The more the merrier? Adjusting fertility to weather shocks

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Abstract

Despite the worldwide decrease in fertility rates, Sub-Saharan Africa is still an exception, showing an almost non-declining trend over the past 50 years. In a high child mortality context parents might prefer a larger number of children, anticipating the risk of child mortality. This paper tests the short-term impact of an exogenous decrease in child mortality on household fertility. By exploiting positive exogenous weather shocks together with household panel data, I find that abundant rainfall increases child survival in the Nigerian context. Large households are the ones who benefit the most from this, and they are also the ones who respond by decreasing their fertility the most. Conversely, small households only slightly benefit from a decrease in child mortality and they continue to increase their birth rate. For a household with the average number of three children, mortality decreases by 0.013 while fertility increases by 0.046 children. When positive shocks occur, households get on average larger, as more children survive and parents only partially reduce their fertility. Consistent with such partial adjustment, household food security and children's anthropometric measures deteriorate. This matches the predictions of the theoretical framework, which shows that the magnitude of the fertility adjustment depends on the number of children alive at the moment of the shock. The empirical analysis tests this prediction, by using the gender of the first-born as instrument for the initial number of children.

Keywords: weather shocks, child mortality, fertility, gender bias, Sub-Saharan Africa, food security

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Introduction

Fertility rates have decreased globally in the past 50 years, falling from 5 to 2 children per woman between 1965 and 2013, according to the World Development Indicators. Yet, fertility rates in developing countries, particularly in Sub-Saharan Africa, are still very high, and have decreased little over the past 50 years. Demographers have long emphasised that having a large number of children can be a rational decision in places where child mortality is still a concrete risk, as is the case for Sub-Saharan Africa.[1] In such contexts, having a buffer stock of children can be a guarantee that at least some of them will survive. Parents might, therefore, anticipate the risk of child mortality with a stock of children, leading to high fertility (Palloni and Rafalimanana, 1999).[2] Yet, causal empirical evidence in support of this mechanism is scarce.

This paper investigates the short-term effects of child mortality on fertility by exploiting an exogenous decrease in child mortality due to temporary positive rainfall shocks. The hypothesis is that parents who already have a hoard of children at the time of the shock will decrease their fertility, as they are getting closer to their desired number of children. Conversely, those with few children will continue to increase their fertility. Using positive shocks allows me to distinguish this mechanism from a pure replacement effect, according to which, parents increase their fertility only when mortality occurs, instead of anticipating it.[3]

The first main finding is that abundant rainfall is a positive shock to children's survival in the Nigerian context, fewer children die and the distance from the desired number of children decreases. It is mostly large households that benefit from such decrease (-0.18 children die for households with four children and -0.35 with five children) and that, in response, reduce their fertility. A household with four children reduces the number of newborns by -0.14 (-0.32 for those with five children), meaning that only those who already have a hoard of children considerably reduce their fertility after a decline in child mortality. For those with the average number of three children, each additional month of positive rainfall shock still slightly decreases mortality (-0.013) while it actually increases fertility (+0.046) three years after the shock.

Hence, the average household becomes larger because more children survive and more children are born three years after the shock. In line with the Quantity-Quality trade-off theory, child health deteriorates. The imperfect fertility adjustment translates into a decrease in household

[1] Despite a declining trend in the past 15 years, Sub-Saharan Africa is still the macro-region with the highest child mortality rates: 89.2 against a world average of 45.6 per 1000 births. Nigeria has the seventh-highest child mortality rate in the world, 116.6 per 1000 births (The World Bank, 2014).

[2] This is one of the hypotheses underlying the demographic transition theory, according to which the decline in fertility follows a decline in mortality (Thompson, 1929). Recent evidence from historical trends in Western Europe casts doubt on the idea that this mechanism is the real and only driver of the demographic transition (Doepke (2005), Galor (2012)).

[3] In this case I would not expect the fertility reaction to a decline in child mortality to differ according to the number of children already alive, as the need for replacement would be reduced equally for all households affected by the shock. Using negative shocks that increase child mortality (such as droughts) do not allow us to distinguish the two mechanisms either, as parents just keep having a positive number of babies in both cases.

welfare in terms of food security.[4] For an average household with three children an additional month of positive rainfall shock still increases food security by 0.028 standard deviations three years later, but the effect turns negative for those with four (-0.49 s.d.) and five (-0.99 s.d.) children. This can be explained by the larger number of surviving children that now need a larger share of food consumption.

These results are in contrast with the standard theory according to which all households should perfectly offset the decline in child mortality, without affecting their overall net fertility rate (Becker and Barro, 1988). The standard theory also excludes the existence of a precautionary demand for children, whereas I find a significant negative correlation between positive past shocks and fertility (both desired and realised), in line with the hoarding hypothesis.

This imperfect adjustment is theoretically explained by two main factors. First, households have not yet reached their desired number of children (on average 7.4, much higher than the real average of three children) at the moment of the shock. Second, the shock is only temporary, not ensuring a future permanent decrease in child mortality. These factors, together with the relatively young age of the mothers, lead to an increase in fertility for households that do not yet have a stock of children. Positive shocks might also have increased women's fecundity thanks to better agricultural harvesting leading to an initial positive nutritional effect. The theoretical model I propose shows that the magnitude of the reproductive adjustment depends, among other factors, on the number of children alive at the moment of the shock. The empirical strategy tests this prediction, by using the gender of the first-born as instrumental variable for the number of children.[5]

The main data source is the nationally representative LSMS-Integrated Survey on Agriculture panel dataset carried out in Nigeria in four waves between 2010 and 2013. The frequency of data collection allows me to test for the effects of the weather shocks immediately after they occur and almost three years later. The longitudinal dimension of the data allows me to explore the effects on child mortality and the fertility response of households according to the number of children at the moment of the shock. Data on climatic variation are drawn from the Standardised-Precipitation Evapotranspiration Index (SPEI), which captures information on the three main parameters affecting agricultural production in a rain-fed crop yields: precipitation, soil evapotranspiration and temperature (Vicente-Serrano et al., 2010). This paper uses rainfall shocks that occurred in the 2010 growing season as an exogenous variation in child mortality.

[4] Given the rural context, household welfare is measured in terms of food security, using a hunger scale that captures both the quantity and quality of food consumption, mainly drawn from the nutritionist literature (see, among others, Coates et al., 2003, Coates et al., 2006 and Deitchler et al., 2010). One of the advantages of using household food security as outcome, instead of consumption per capita, is that it does not depend mechanically on household size, which is the regressor of interest. I have quantitatively assessed the validity of this hunger scale in a previous work (Bertelli, 2013).

[5] Son-preference in Nigeria has been analysed in the anthropological literature, such as Izugbara and Ezeh (2010), Fayehun et al. (2010), Isiugo-Abanihe (1994) and Fapohunda and Todaro (1988). Milazzo (2014) has also recently shown with DHS data the existence of son-preference in the Nigerian population, where the birth of a girl as first-born child pushes households to shorten birth spacing and to increase the number of ever-born children in order to have a son. The analysis conducted by Milazzo (2014) also suggests the existence of a replacement effect among Nigerian households. She finds that those with a dead *male* first-born have, on average, 0.5 more births than those with a dead *female* first-borne.

This paper relates to the demographic and sociological literature that has tested the decline in child and infant mortality as one of the mechanisms that might have triggered the demographic transition. While it is plausible that in the long-term a decrease in child mortality might reduce fertility rates, empirical evidence remains mixed. Several empirical analyses have revealed a positive correlation, (see, among others, Freedman, 1975 and Ben-Porath, 1976), but have not succeeded in solving identification issues related to omitted variable bias and confounding factors. Micro-simulation exercises conducted by Fernandez-Villaverde (2001) and Boldrin and Jones (2002), based on English data between the 16th and 20th centuries, show that a small reduction in infant mortality increases both fertility and population growth rates. Doepke (2005) finds similar results with English data between 1861 and 1951, but in many cases there is no clear pattern (Van de Walle (1986) and Galloway et al. (1998); for a discussion see Doepke (2005) and Galor (2012)). More recently, Bhalotra et al. (2014) exploited an exogenous decrease in child and maternal mortality resulting from the introduction of antibiotics in the US. The authors find that lower maternal and child mortality both led white women (but not black women) to reduce their fertility.

The current paper differs from the existing literature in that it focuses on the short-term impact of an exogenous temporary positive shock on fertility, allowing me to identify causal impacts. At the same time, I also account for past shocks that could have longer term consequences, capturing the hoarding mechanism. In contrast to the past literature on the demographic transition, it does not aim to say anything causal about past long-term shocks, for which the causal impact is more difficult to identify. Moreover, to the best of my knowledge, so far, the impact of child mortality on fertility has not yet been explored in the context of developing countries using panel micro data and a valid identification strategy.

This paper also relates to the empirical microeconomic literature investigating the reasons for the persistence of a high-fertility behaviour. One of the first aspects analysed by this literature is the lack of contraceptive methods. Pörtner et al. (2013) show that, on average, access to contraception does not reduce fertility in Ethiopia, or only for the least educated women, suggesting that education is a substitute for contraception. Similarly, Miller (2010) finds that the higher access to contraception provided by the Colombian *Profamilia* Conditional Cash Transfer explains less than 10% of Colombia's fertility reduction. These studies, together with several others,[6] suggest that it is not a matter of lack of supply, but rather of lack of demand for contraceptives.

The lack of demand could, in part, be explained by the persistence of social norms and beliefs that prohibit the use of contraception and favour high fertility. Munshi and Myaux (2006) study the Matlab family planning program and indicate that the delay in the transmission of information and adoption of contraception is due to the social norms that regulate both fertility practices and women's networks. The importance of women's networks for the adoption of contraceptive practices is also documented by Comola (2008) in the Nepalese context. Social

[6] The shortcoming of studies evaluating family planning programs is usually the lack of adequate identification strategies due to the non-random assignment of the programs. Pörtner et al. (2013) deal with this by using an instrumental variable approach, while Miller (2010) relies on the random assignment of *Profamilia*.

norms are not, however, immutable and can change over time. This is the case for Brazil where social media have helped change social norms relating to fertility, effectively lowering the number of births (La Ferrara et al., 2012). Women's lack of empowerment or independence with regard to contraceptive decisions might also play a role in the low demand. Ashraf et al. (2014) show that when family planning services reach women without the presence of their partner there is a substantial increase in the take up of contraceptives, resulting in decreased birth rates.

Another strand of the literature has brought to light the strategic behaviour behind the fertility decision. In Senegal, mothers explicitly increase the number of newborns the have, aiming in particular at having a son, as an insurance strategy against widowhood (Lambert et al., 2014). The insurance aspect of fertility has also been shown by Banerjee et al. (2014) in China, where higher aggregate fertility is associated with lower savings, in line with the old-age pension theory, according to which the more children a couple has, the less they need to save for their old age, as their children will take care of them.

In conclusion, while the current literature about the effects of child mortality on fertility has focused on long-historical trends leaving identification issues unresolved, this paper contributes to the literature on reproductive behaviour by concentrating on a relatively short-term analysis of the effect of a fall in mortality on fertility behaviour. First, it explicitly addresses both theoretically and empirically the impact of child mortality on fertility in a developing country using panel micro data. Second, it exploits two exogenous variations (the gender of the first-born child and weather shocks) to evaluate the impact of a fall in child mortality on reproductive behaviour. Third, by exploiting a rich longitudinal dataset, it shows the welfare effects of the fertility adjustment in terms of household food security.

These results indicate that in high-mortality and risky environments, such as Nigeria, households seem to opt for a stock of children, so as to ensure that at least some of them will reach adulthood. The design and cost-effectiveness evaluation of family planning policies should take into account this capacity of households to adjust their fertility behaviour. Moreover, in places where child mortality is still high, policies directly aiming to changing fertility behaviour might be less successful as parents might not be willing to reduce their fertility.

The remainder of this paper is organised as follows. Section 1 presents the theoretical framework concerning the fertility decision given a positive shock on child survival. Section 2 describes in detail the data used, discusses the sample selection and provides some descriptive statistics about fertility, weather shocks and food security. Section 3 introduces the identification strategy adopted. Section 4 provides the main results in terms of reproductive behaviour and food security. Section 5 investigates the robustness of the main specification and Section 6 concludes.

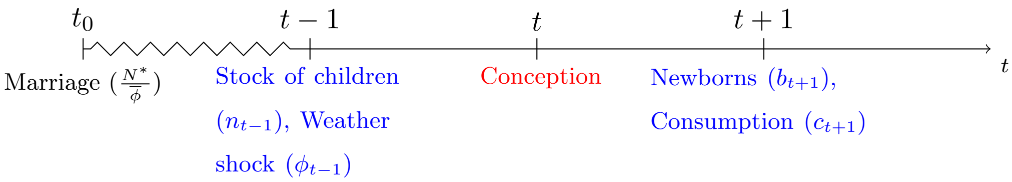
1 Theoretical framework

The links between mortality and fertility have long been investigated by the literature on the demographic transition, traditionally looking at long-term macro changes in fertility and mortality rates either within or across countries. In line with this literature, micro-founded Beckerian theory suggests that these two phenomena can be positively related, a decline of child mortality increasing the probability of survival and reducing the number of births (Becker and Barro, 1988). Recent quantitative evidence from simulation results of the beckerian model and historical trends of child mortality and fertility in Western Europe has instead indicated a negative relationship (Doepke (2005), Galor (2012)).

In line with this literature, this paper focuses on the effects of a fall in child mortality exploiting a positive exogenous rainfall shocks. My theoretical framework shows that this brings parents closer to their target of number of children.[7] Those households that are still far away from their preferred number at the moment of the shock will respond by only partially reducing their fertility. In turn, fertility will tend to zero for those that already have a stock of children.

In addition, looking at past positive climate shocks allows me to disentangle the hoarding from the replacement mechanism. If the hoarding motive is predominant in Nigeria, then in places where a large number of positive rainfall shocks has decreased child mortality, parents should desire fewer children, as there is no need to anticipate child mortality, and have on average a lower fertility. If, in turn, the replacement motive is predominant, then no significant correlation should exist between the desired number of children and past climate shocks, as parents should only have a lower number of births but no different preferences.

Fertility choice. The following model examines the household choice of having an additional child. It is framed in a dynamic setting, with $t = 0, .., T$ periods, t_0 being the date of marriage. Past shocks are defined as those occurring between t_0 and $t-1$, while recent shocks are at time $t-1$. Past and recent weather shocks are i.i.d. The number of children that has survived past and recent shocks is observed by parents at time t. Conception occurs at time t and births take place at time $t+1$. Food security is observed at both time t and $t+1$. The model time-frame is sketched as:



Parents express at time t_0 their preferred number of surviving children (N^*). Their target is based on their past experience of shocks ($\overline{\phi} = \sum_{t=0}^{t-1} \phi_t$, with ϕ_t being the weather shock at time t) and is not affected by recent shocks. As parents are risk-adverse, the lower the average probability of child survival, the larger their ideal family size, because of the hoarding effect: $\frac{N^*}{\overline{\phi}}$.

[7] The existence of a hoarding motive in this context is plausible given the persistent high fertility and child mortality rates. Fertility slightly varies across the country, ranging from 7.2 in the north-east to 4.5 in the south-west (National Population Commission (NPC) [Nigeria] and ICF Macro, 2009).

In each period, parents observe the number of children alive and the distance from their ideal family size. The decision to have an additional child is characterised by a trade-off between choosing one more unit of consumption in the short run or having one more child in the next period to get closer to the ideal number.

Households have a stock of surviving children at time $t-1$, which is given.[8] At the same time a positive rainfall shock (ϕ_{t-1}) occurs increasing the proportion of children. The number of surviving children at t is equal to $n_t = \phi_{t-1} n_{t-1}$. Parents care about the number of surviving children and, in particular, about their relative distance from the target, expressed as $d_{n,t} = n_t - \frac{N^*}{\bar{\phi}}$.

At that point in time, they decide whether to have more children or not. If the mortality reduction caused by the shock allows them to achieve the desired target (i.e. $d_{n,t} = 0$), then no new pregnancy will start at t and there will be no newborns at time $t+1$. This is the largest adjustment. If the difference between the actual number and ideal number is still negative, there will be newborns at time $t+1$, making the adjustment smaller. Eventually, the difference will reach zero and parents will increase their utility from their own consumption and the number of children alive.[9] Households benefiting from positive shocks will hit their target earlier than other households.

The larger the number of children at time $t-1$, the smaller the distance from couple's ideal family size, hence the larger the marginal benefit of a child mortality reduction and the larger their adjustment (i.e. they are more likely to respond perfectly by having no newborns). Those at the beginning of their fertility history (close to t_0) are still far away from their desired family size, making the marginal benefit of a mortality reduction lower and the adjustment much smaller, by continuing to have a non-null number of newborns.

The future number of children is given by the sum of the children that have survived the shock plus future births:

$$n_{t+1} = (\phi_{t-1} n_{t-1}) h_{t-1} + b_{t+1} \tag{1}$$

The children who are alive have a child-specific probability of surviving until the next period, which is proxied by their health conditions h_{t-1} as affected by the shock.

Household utility is a function of adult consumption (c_t, proxy for food security) and the distance from the ideal target ($(\phi_{t-1} n_{t-1}) - \frac{N^*}{\bar{\phi}}$). The number of children enters the household utility function because parents' utility increases with the number of surviving children, until reaching N^*. I assume a concavity in the increasing utility from the number of newborns when approaching the desired size. The closer parents are to their ideal family size, the lower the marginal utility of an additional newborn. That said, given that I focus on young households where the mother's average age is 26 years, it is not completely unrealistic to think that newborns

[8] The empirical strategy takes into account the endogeneity of the initial number of children with an instrumental variable approach.

[9] Because fertility is biologically limited in time, it is possible that households do not manage to reach their target and $d_n < 0$ at the end of a couple's period of fertility. In this setting, I consider only $t < K$, K being the biological time limit of fertility.

might increase household utility in a linear way. Utility is modelled as a CES function:

$$U(c_{t+1}, b_{t+1}) = \{\beta(c_{t+1})^\rho + (1-\beta)[h_{t-1}(\phi_{t-1}n_{t-1}) + b_{t+1} - \frac{N^*}{\overline{\phi}}]^\rho\}^{1/\rho} \tag{2}$$

for $\rho \leq 1$ and $1 \leq \beta \leq 1$. The larger the positive shock in $t-1$, the more surviving children there are at time t. For a given number of surviving children, the distance from the desired number decreases if they have a good probability h of surviving to the next period.

The budget constraint is made of adult consumption expenditures and the cost of raising children (including births, n). This has a 'monetary' component α_t (food, education, clothes) and a time opportunity-cost given by the time dedicated by parents to children when not working $(1-\theta)y$, with θ being the working time share. The budget constraint is:

$$c_{t+1} + [(\phi_{t-1}n_{t-1}) + b_{t+1}][\alpha_t + (1-\theta)y_t] = y_{t+1} \tag{3}$$

In line with the Quantity-Quality trade-off theory, the investment in children $(\alpha_t + (1-\theta)y_t)$ decreases when their number increases $(\phi_{t-1}n_{t-1})$, for a given budget constraint.

The CES share parameter β expresses the effect of decreasing adult consumption in t on the distance between the number of living children and the desired number. The elasticity of substitution $1/(1-\rho)$ captures the trade-off faced by parents between increasing consumption and getting closer to their desired number. For a CES utility, ρ represents the degree of substitutability between those two options.

Thanks to the positive weather shock, the number of surviving children increases, reducing the distance from the preferred number. If $\rho \to -\infty$, getting closer to the preferred number is not a substitute for adult consumption. If ρ is negative, adults should respond by decreasing their own consumption as well. If $\rho \to +\infty$, the two are substitutes, hence the reduction in the distance between the actual and the desired number of children allows parents to increase their own consumption.

If $-\infty < \rho < 1$, the optimal ratio is given by the following solution. Re-writing the current investment in children as $\alpha_t + (1-\theta)y_t = I_{t-1}$, the problem the household solves is:

$$\begin{aligned} \underset{c_{t+1}, b_{t+1}}{\text{Max}} \quad & \{\beta c_{t+1}^\rho + (1-\beta)[h_{t-1}(\phi_{t-1}n_{t-1}) + b_{t+1} - \frac{N^*}{\overline{\phi}}]^\rho\}^{1/\rho} \\ & s.t. \quad c_{t+1} + (\phi_{t-1}n_{t-1}) + b_{t+1}I_t = y_{t+1} \end{aligned} \tag{4}$$

I specify a Lagrangian function, with λ being the Lagrangian multiplier and, to simplify the notation, I replace $\phi_{t-1}n_{t-1} = n_t$:

$$L = [\beta c_{t+1}^\rho + (1-\beta)(n_t h_{t-1} + b_{t+1}) - \frac{N^*}{\overline{\phi}})^\rho]^{1/\rho} - \lambda(c_{t+1} + n_t + b_{t+1}I_t - y_{t+1}) \tag{5}$$

Simplifying the objective function:

$$A = \beta c_{t+1}^{\rho} + (1-\beta)[h_{t-1}(n_t + b_{t+1}) - \frac{N^*}{\bar{\phi}}]^{\rho} \tag{6}$$

Maximising with respect to c_{t+1} and b_{t+1} gives:

$$\begin{aligned} \frac{\delta L}{\delta c_{t+1}} &= 0 \\ \frac{1}{\rho} A^{\frac{1}{\rho}-1} * \rho\beta(c_{t+1})^{\rho-1} - \lambda &= 0 \\ \frac{\delta L}{\delta b_{t+1}} &= 0 \\ \frac{1}{\rho} A^{\frac{1}{\rho}-1} * \rho(1-\beta)[h_{t-1}(n_t + b_{t+1})]^{\rho-1} - \lambda I_t &= 0 \end{aligned} \tag{7}$$

From which I find:

$$\frac{b_{t+1}}{c_{t+1}} = (I_t \frac{\beta}{1-\beta})^{1-\frac{1}{\rho}} - (\phi_{t-1} n_{t-1}) h_{t-1} \tag{8}$$

From Equation 8 three main factors determine the number of newborns:

1. The more children that have survived the shock, the lower the number of newborns.
2. Investments in children do not increase linearly with the number of surviving children, but show economies of scale for $\rho > 1$. This means that households with low n_{t-1} will increase their fertility relatively more than those with a large number of initial children after a positive shock, as the right-hand side difference decreases as the number of children rises.
3. Adult consumption might decrease or increase, depending on the initial number of surviving children and the increase in child survival.

Hence, parents might choose not to adjust their fertility perfectly to the weather shock, meaning that they will still have a positive number of newborns, despite the reduction in child mortality. At time $t+1$, they will have more children and a tighter resource constraint, with lower adult consumption. The choice between having more newborns or buffering more young children against food security will depend on the uncertainty about the future survival capacity of the marginal children and the degree of substitutability between adult consumption and reaching the desired target.

The model generates four testable predictions about the consequences of a positive shock:

1. The number of dead children decreases
2. The gap between actual and ideal family size is reduced, given the increased number of surviving children

3. On average fertility increases, but the less so the larger the number of children at the time of the shock

4. The change in adult consumption depends on the degree of substitution with the number of children and newborns.

Finally, the model also predicts that households living in riskier environments (i.e. suffering more from negative weather shocks) have precautionary demand for children.

In Sections 4 and 5 I apply the predictions to the data. After showing that positive weather shocks reduce child mortality, I use such shocks as exogenous variation in survival probability ϕ_{t-1}. By instrumenting n_t with the gender of the first-born, I test the effect of $\phi_{t-1}n_t$ on the number of newborns three years after the shock occurs (b_{t+1}). Using the information provided in the 2013 Demographic and Health Survey data I also test the effect of rainfall on children's anthropometrics, as a proxy for child quality (h_t). In addition, I investigate the effect on the desired number of children declared by parents, looking at the distance between the desired size and the actual number of living children ($n_t - \frac{N^*}{\overline{\phi}}$). By considering past shocks that have occurred over the previous thirty years ($\overline{\phi}$), I test the hoarding hypothesis.

2 Data and Descriptive Evidence

This study investigates fertility decisions by exploiting a positive exogenous shock on child survival in Nigeria. Using longitudinal data, I look at the effects of weather shocks on child mortality and the response of household fertility three years after. The World Bank LSMS-Integrated Survey on Agriculture household panel data and the SPEI-Index database represent the two principal data sources. In addition, I use the Nigeria Demographic and Health Survey 2013 data for a number of specifications and robustness tests. The following subsections describe the data used and provide some descriptive statistics of the sample.

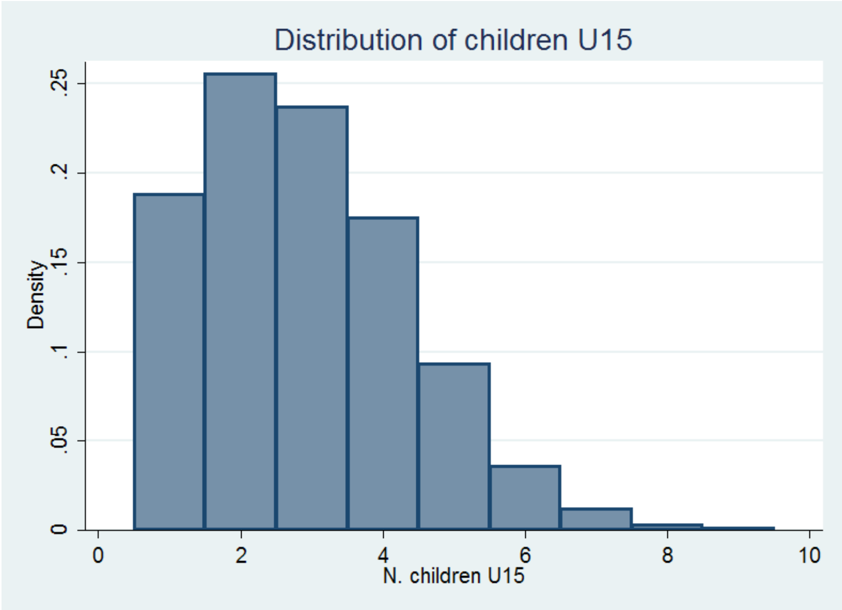
2.1 Number of children and food security. The Nigeria LSMS-ISA data.

The first main data source is the nationally representative LSMS-ISA data panel for Nigeria, collected in two rounds in 2009/10 and 2012/13. In each round, data was collected before (September) and after (March) the harvest season, for a total of four waves.[10] The LSMS-ISA panel data represents the main source of information regarding the measurement of the number of children and household food security.

Number of children. I focus on young children under 15 years old living in the household at the moment of the first survey (September 2010) and for whom both biological parents

[10] The overall panel consists of 4986 households in the first wave, 4851 in the second and 4716 in each of the last two waves, with 4671 being interviewed in all four surveys.

Figure 1: Distribution of the number of children U15, mothers under 35 years old.



are present.[11] To ensure that this definition is a good proxy for the actual number of living children, the sample is restricted to households with mothers under 35 years old, for whom it can be reasonably assumed that the great majority of their living children are still at home. This is the same age cut-off adopted by Angrist and Evans (1998) with the USA census data.[12] In the selected sample on average, a mother has 2.9 children under 15 years old, the median number being 3, the minimum 1 and the maximum 9 (see Figure 1). Children are on average 7.7 years old, while the first-born child is on average 8 years old.

The analysis considers the number of children that were born, and the number of children that died, between the first and last survey rounds (2009 and 2013). In the rest of the paper, I refer to these as the number of newborns and dead children. They were born in 2011 (47.6%), 2012 (46.8%) and 2013 (1%), for the remaining 4.6% the information on date of birth is missing. In 2013, 46.9% of newborns are aged below one year old, 36.76% are one year old and 12.9% are two years old. The dead died between the two survey rounds, but no additional information about the date nor age at death is provided in the data. Looking at the date of birth suggests that 65% of the children who died were under the age of 8.

Food security. To investigate the consequences of the fertility response, and given the rural context, food security is used as a measure of household welfare. It is expressed in terms of a nine-item scale, capturing the psychological fear and the qualitative and quantitative aspects of food

[11] This limits the sample to couples having at least one biological child under 15 years old, excluding single-headed households and second-generation children (grand-children), while including both monogamous and polygamous households. By selecting couples the sample might show fewer households with a female first-born than when including single-parents households, as some studies have shown that the risk of divorcing increases if the first-born is a girl (the order of magnitude is always very small (0.1-0.5%), see Hamoudi and Nobles (2014)).

[12] Table A.1 provides the main estimates for mothers under 30 and shows that the results are driven by the sample of younger mothers.

insecurity and constructed following the nutrition literature.[13] Based on qualitative interviews describing the hunger experience of households and individuals, this type of scale combines answers to various specific questions capturing the different dimensions in a quantifiable "hunger scale".

The great detail of the LSMS-ISA data about agricultural activity is enriched by the pre and post harvest dimensions, which are relevant for investigating food security conditions. Food insecurity, so measured, is a quite common condition in the Nigerian sample. Almost 40% of the respondents report suffering from food insecurity related to the quality of food (first two items, Table A.2). One third is moderately food insecure, having suffered from lack of food quantity in the previous week and finding themselves obliged to cut the amount or the frequency of meals during the day.[14] In the rural context analysed, two thirds of the households consume some home-grown food, making the farm's harvest a vital resource for achieving food security. Indeed, households appear more secure after the harvest, reporting all nine items significantly less often (see the means-test in Table A.2, Column 3).[15] In what follows, and for ease of interpretation, I convert the food insecurity scale into a food security one and use the z-score. See the Appendix for more details.

2.2 Realised and preferred fertility. The Nigeria DHS data.

The Demographic and Health Survey collected in Nigeria in 2013 provides information about the birth history of each surveyed woman.[16]In contrast to the LSMS-ISA data, the DHS consider all children ever born, alive or not, which makes it particularly useful for two main reasons. First, by selecting the same sample as for the LSMS-ISA, I investigate potential biases that might come from looking only at the children living in the household at the moment of the survey (see discussion in Section 3.1). Second, they allow me to test the second model predictions, according to which the gap between the desired and actual number of children decreases after a positive weather shock. In addition, I can investigate the impact of the shock on the average health status of children by using anthropometric measures.

The figures for the number of children from the LSMS-ISA and DHS data are very close. On average, in the selected LSMS-ISA sample, a married woman under 35 has 3.0 children under 15,

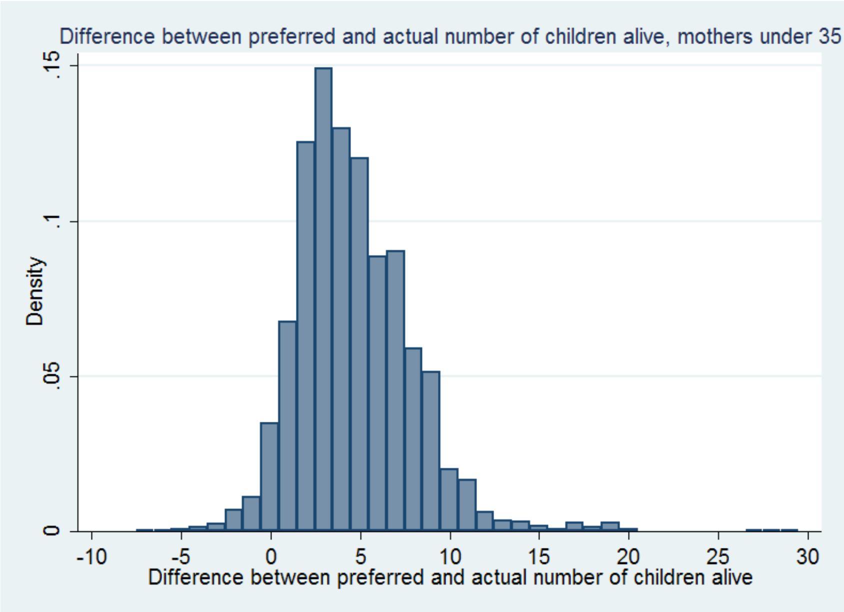
[13] For a review of the main studies see Coates et al. (2003), Coates et al. (2006) and Deitchler et al. (2010).

[14] This aspect of the scale could be compared to the FAO's Food Inadequacy measure, which also includes those who, even though they cannot be considered chronically undernourished, are likely being conditioned in their economic activity by insufficient food. The statistics for Nigeria report a much lower percentage of Food Inadequacy, at 11,9% for the 2011-2013 period.

[15] The pre-harvest season is the most severe time of year in terms of food insecurity. Almost two households out of ten reduce adults' meals for the sake of their children and 11% ask relatives and friends for help. One out of ten is severely food insecure, having no food at all and going to sleep at night without eating. Such a percentage is in line with the Prevalence of Undernourishment measure estimated by the FAO at 7.3%.

[16] The Nigeria Demographic and Health Survey (DHS) consists of a nationally representative sample of 40.320 households in which there is at least one woman aged 15-49. The main objective of the survey is to provide reliable information on fertility, contraception, maternal and child health and mortality, women's empowerment and domestic violence (National Population Commission (NPC) [Nigeria] and ICF Macro, 2014). The share of rural households is slightly lower than for the LSMS-ISA data, 58.83% against 67.7%. Both datasets are representative at the national and urban/rural level, but DHS respondents are only women aged 15-49 and their husbands.

Figure 2: Distribution of the difference between the preferred and the number of children alive, mothers under 35 years old.



in line with the 2.8 reported in the 2013 DHS.[17] By looking at the preferred number of children expressed by women, the DHS data show that for the selected sample the distance between preferred and actual number is on average 4.69 (median 4, first quartile 2, third quartile 10, see Figure 2).[18] This is in line with the ideal number of children being 7.5 and the average number of living children being 5.38. This means that the majority of households are still quite far away from their target, although, given that the average age of mothers is 26.6 years, it is not out of reach.

2.3 Weather shocks. The SPEI Index.

The second main data source concerns weather data and relies on the Standardised-Precipitation Evapotranspiration (SPEI) Index (Vicente-Serrano et al., 2010), which combines data about temperature, precipitation and evapotranspiration from the soil.[19] The Index is available up to December 2012 and is expressed in monthly standard deviations from the historical mean at a 0.5 arcdegree level, corresponding to an area equal to 52 km^2.[20] It is at that level that I define

[17] Completed fertility in Nigeria is higher: in the selected DHS sample the average number of ever-born children is 6.9.

[18] In the 2013 DHS entire sample husbands desire on average 9.3 children, which is more than women want in 43% of the cases.

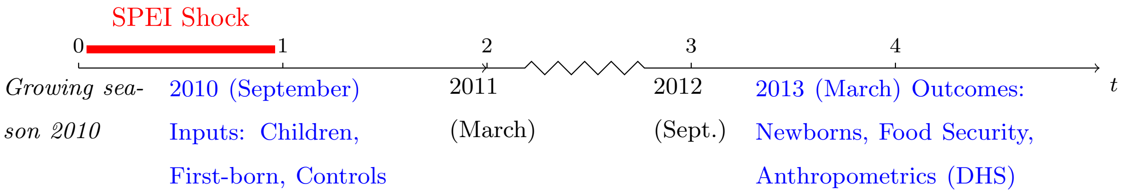
[19] This study does not take into account self-reported shocks that have caused household to lack food, although they are available in the LSMS-ISA data. The main reason being that the correlation with the SPEI-Index is tiny (around 0.05) although positive, showing, for instance, that where droughts have occurred a higher share of people report having lacked food in the previous 12 months. In turn, the correlation between self-reported droughts and the SPEI-Index goes in the opposite direction, with a lower share of people reporting poor rain where droughts have actually occurred.

[20] The final sample has 168 GPS-cells (162 with no missing information), with an average of 12 observations per cluster. Out of the 168 clusters, 74 are in the Tropical-warm/semiarid zone, 79 in the Tropical-warm/subhumid one, 13 in the Tropical-warm/humid one and 2 in the Tropical-cool/subhumid zone.

covariate weather and climate shocks.

Positive shocks (abundant rainfall) are defined in terms of the number of months in the growing season (from February to August, depending on the Agro-ecological zone) with a SPEI Index[21] between +1 and +2 s.d.[22] They concern 60.8% of the sample, having on average one month of the growing season with abundant rainfall. Likewise, a negative weather shock (drought) is defined as the number of months during the growing season with a SPEI Index below -1 standard deviations. Droughts concerned 45.6% of the selected households, lasting on average three weeks. Only 9.5% of the analysed sample was not affected by either droughts or abundant rainfall, while 15.8% was affected by both.

The following time-line shows the four LSMS-ISA waves, together with the SPEI data, highlighting in which wave the main variables of interest are measured:



The geographical distributions of the shocks are presented in Figure 3, showing droughts (panel A) and abundant rainfalls (panel B). Droughts have occurred across the country, in the southern, eastern and western states. The northern region, more arid than the rest of Nigeria, had a rainy growing season in 2010 compared to its historical mean, together with the east and center. The east and part of the central regions were characterised by both dry and rainy spells during the sample period.

During the six months of the growing season, positive weather conditions in April, July and August increase harvest quantity, while droughts in June is negatively correlated with harvest quantity (Graph A.8). [23] Overall, droughts appear to be negatively correlated with the amount and value of harvest sold, whereas abundant rainfall is significantly associated only with an increase in the quantity of harvest sold, but not with its value(Table A.3).[24]

[21] The SPEI database provides the already computed standard deviations, see Vicente-Serrano et al. (2010) for the methodology. Using standard deviations from the historical mean at the grid level allows me to capture weather variations that are meaningful for the local conditions of the same grid. For a discussion on how to measure weather and climate shocks, see Dell et al. (2014) and for a similar approach with the same data, see Harari and La Ferrara (2013).

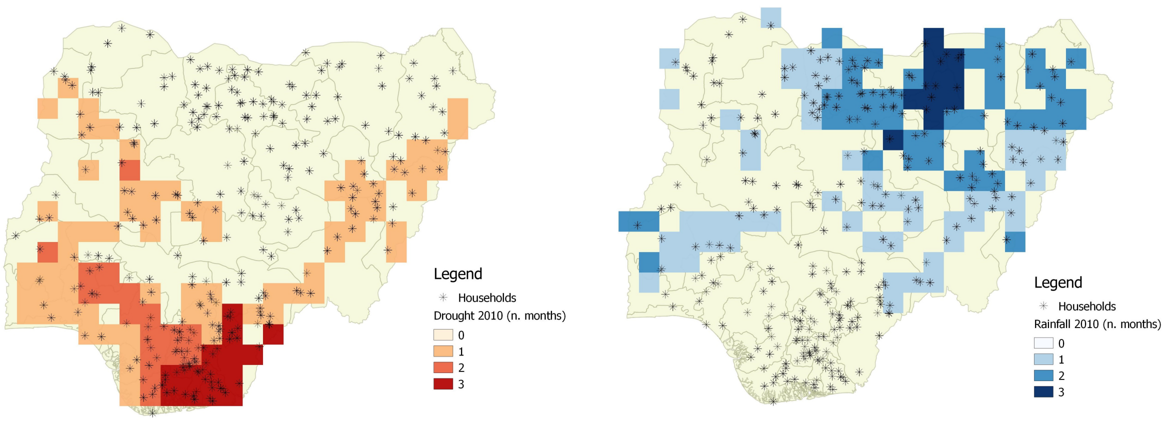
[22] Standard deviations above 2 indicate extreme floods and concern 11% of the sample.

[23] Coefficients are estimated by controlling for household characteristics and for the spatial lag of the dependent variable and disturbance term. Adjusting for spatial correlation reduces the noise and decreases the standard errors.

[24] To check the price effects of weather shocks, where the shock could affect changes in local relative prices, I regress the price of the main crops cultivated in the dataset as extrapolated from the community questionnaire on the climate shock, controlling for State fixed effects, as markets could be locally integrated (as in Duflo and Udry (2004)). The prices of some items are significantly related to the dry and wet spells (Table A.4 and A.5). In particular, the prices of maize (both white and yellow) and fresh fish increase in times of droughts, while those of plantain increase with abundant rainfall.

Figure 3: Weather shocks in 2010

(a) Dry months (b) Rainy months



3 Empirical Strategy

In this section, I test the predictions of the theoretical framework, looking at the effects of positive weather shocks on the fertility decisions and the implications in terms of food security.

To test predictions 1 and 2 I explore the average effect of the weather shock per se, using an OLS specification:

$$Y_{i,t+1} = \alpha_0 + \alpha_1 Shock_{c,t-1} + \phi_1 E_{i,t-1} + \phi_2 F_i + \chi_z + \eta_{c,z} \tag{9}$$

To investigate whether the fertility adjustment depends on the initial number of children and the implications for food security (predictions 3 and 4), the specification is the following:

$$\begin{aligned} Y_{i,t+1} = \gamma_0 + \gamma_1 \widehat{Children}_{i,t-1} + \gamma_2 \widehat{Children_{i,t-1} *} Shock_{c,t-1} + \gamma_3 Shock_{c,t-1} + \\ \phi_1 E_{i,t-1} + \phi_2 F_i + \lambda_z + \theta_{c,z} \end{aligned} \tag{10}$$

The main outcome variable is the number of newborns, measured at the household level (i) in the fourth wave (March 2013). The theoretical model predicts that the larger the number of children at the time of the shock the fewer newborns two years later, making the interaction γ_2 one of the main coefficients of interest, together with γ_3. To establish the prior step, I also estimate the same model with the number of children that died between 2010 and 2013 as the outcome variable.

The shock ($Shock_{c,t-1}$) is a categorical variable indicating the number of abnormal months during the 2010 growing season, as defined in Section 2.2. The focus of this paper is on temporary positive rainfall shocks, but to control for climate risk, and to check for serial correlation of weather shocks, I include the mean of past shocks that have occurred in the same grid in the previous 30 years, between 1980 and 2009. The interpretation of the estimated coefficient on past shocks is not causal, but a mere correlation. These climate shocks capture $\overline{\phi}$, as defined in the theoretical model, and are in line with the hoarding hypothesis.

The coefficient γ_1 captures the effect of an additional child for counterfactual group, meaning those households that did not benefit from abundant rainfall in 2010. The coefficient of interest is γ_2 (summed together with γ_3), the interaction between the current number of children and weather shocks. This corresponds to $\phi_{t-1}n_{t-1}$ in the theoretical framework. The coefficient of γ_3 alone indicates the effect of the 2010 weather shocks for those households with one child.[25]

I control for households and mother's characteristics, time-invariant (F_i) and time-varying ($E_{t,i-1}$), including: assets' value (defined before the shock), mother's age (and squared term), education and rank (higher than one for polygamous households), father's education, set of three dummies for the prevalent ethnic group at the grid-level,[26] age of the first-born, distance to the nearest population center (in km) and the z-score of the gender ratio of sons and daughters under 15 years old.

The specification includes controls for the Agro-ecological zones, which capture time-invariant unobservable soil characteristics and climate patterns (η_z).[27] The standard errors ($\epsilon_{c,z}$) are clustered at the grid level (i.e. treatment level) and the fixed effect level to allow for correlation across grids within the same Agro-Ecological zone (Cameron and Miller, 2015).

In order to avoid selection issues in the endogenous choice of parents of having children, the sample only includes households with at least one biological child under 15 years old. However, the number of children living in the household, the decision to have more children, and child mortality, might all be affected by observable characteristics, such as wealth, parents' education, mother's age and religion, and also by preferences and tastes that are unobservable in the data.

Such endogeneity is addressed by using the gender of the first born as an instrument for the number of children, following the literature on son preference. Assuming random assignment of the gender of the first born, if parents have a preference for boys, they may adjust their fertility upwards if the first child is a girl. Milazzo (2014) shows that in Nigeria mothers with a first ever-born baby girl have 0.07 more children than those with a first ever-born boy and those between 30 and 49, closer to the end of their fertility, have 0.11 more ever-born children.

The LSMS-ISA data do not provide any information on the entire birth history of each woman, but only report detailed characteristics of the children living in the household at the

[25] The number of children is standardised as the number of children minus one, the minimum in the sample, so to interpret the γ_3 coefficient as the shock for those with one child.

[26] Information about ethnicity is not collected in the LSMS-ISA data. However, it is available in the Nigeria 2013 DHS, which I use to determine the predominant ethnic group at the grid-level. I create a set of dummies capturing the predominant group at the grid-level for the Hausa-Fulani, Iqbo and Yoruba groups. The Hausa-Fulani represent 46% of our sample and are in the whole of the northern region, the Igbo constitute 10% of the sample and are located in the South-East, whereas the Yoruba (3%) are concentrated in the South-West.

[27] The Agro-ecological zones in Nigeria are divided into Tropic-warm semi-arid, tropic warm sub-humid, tropic-warm humid and tropic-cool sub-humid. Such information is provided in the LSMS-ISA data based on the WorldClim climate data and 0.0833dd resolution (approximately 10x10 km) LGP data from IIASA. As explained by Sebastien (2014) in the IFPRI Atlas on African Agriculture (p.34), "Agroecological zones (AEZs) are geographical areas exhibiting similar climatic conditions that determine their ability to support rainfed agriculture. At a regional scale, AEZs are influenced by latitude, elevation, and temperature, as well as seasonality, and rainfall amounts and distribution during the growing season. The resulting AEZ classifications for Africa have three dimensions: major climate (tropical or subtropical conditions), elevation (warmer lowland or cooler upland production areas), and water availability (ranging from arid zones with less than 70 growing days per year to humid zones where moisture is usually sufficient to support crop growth for at least nine months per year)."

moment of the survey, or who have left in the last 12 months. The gender of the first born is thus proxied by the gender of the oldest child living in the household.[28] Both $Children_{i,t-1}$ and $Children_{i,t-1} * Shock_c$ are instrumented with a dummy equal to one if the first child is a girl ($Firstborn_i$) and its interaction with the shock ($Firstborn_i * Shock_{c,t-1}$). The first stage of the 2SLS estimator is:

$$\left.\begin{array}{r} Children_{i,t-1} \\ Children_{i,t-1} * Shock_{c,t-1} \end{array}\right\} = \beta_0 + \beta_1 Firstborn_i + \beta_2 Firstborn_i * Shock_{c,t-1} + \beta_3 Shock_{c,t-1} + \\ \delta_1 E_{i,t-1} + \delta_2 F_i + \mu_z + \upsilon_{c,z} \tag{11}$$

Food security regression. The food security regression corresponds to Equation (10), controlling in addition for the initial condition in 2011 ($y_{i,t}$):

$$\begin{aligned} Y_{i,t+1} = \gamma_0 + \gamma_1 Children_{i,t-1} + \gamma_2 Children_{i,t-1} * Shock_{c,t-1} + \gamma_3 Shock_{c,t-1} + \gamma_4 y_{i,t-1} + \\ \phi_1 E_{i,t-1} + \phi_2 F_i + \lambda_z + \theta_{c,z} \end{aligned} \tag{12}$$

3.1 Identification challenges

This section discusses the main identification challenges posed by the empirical analysis. First, I explain ways of dealing with possible violations of the exclusion restriction. Second, I consider issues concerning the exogeneity of the gender of the first-born child and weather shocks.

Exclusion restriction. The exclusion restriction assumption can be violated if there are other channels through which the gender of the first-born might affect fertility and child mortality, rather than through the initial number of children and its interaction with the weather shock. For instance, mothers might delegate some domestic chores to the first-born if she's a girl, freeing time for the mothers, which is one of the main factors concerning the fertility choice (see, for instance, Angrist and Evans (1998)). This can only be the case if the first-born is old enough to take care of such domestic chores. Controlling for the age of the first-born helps reinforce the exclusion restriction, meaning that it is the actual effect of the gender of the first born and not his/her age that makes parents have more children.

In addition, for rural households dependent on agricultural activity, having a female or male first-born might affect food security directly if there is a different gender productivity of children in agricultural work.[29] I address this issue by controlling for the children's gender-ratio,

[28] The 2SLS estimator allows me to estimate a LATE effect for those households with son preference, which I find to be driven by the sample of mothers with very low education levels (primary school) or no education at all. The instrumental variable identifies the number of children under 15 years old that are in common to both parents and still living in the household. Moreover, it assumes that the effect is monotonic irrespective of the number of children.

[29] For instance, Paxson (1992) finds that a higher number of males aged 12-17 increases income of farmers much more than the number of females in the same age group.

capturing whether a household has a majority of boys or not.

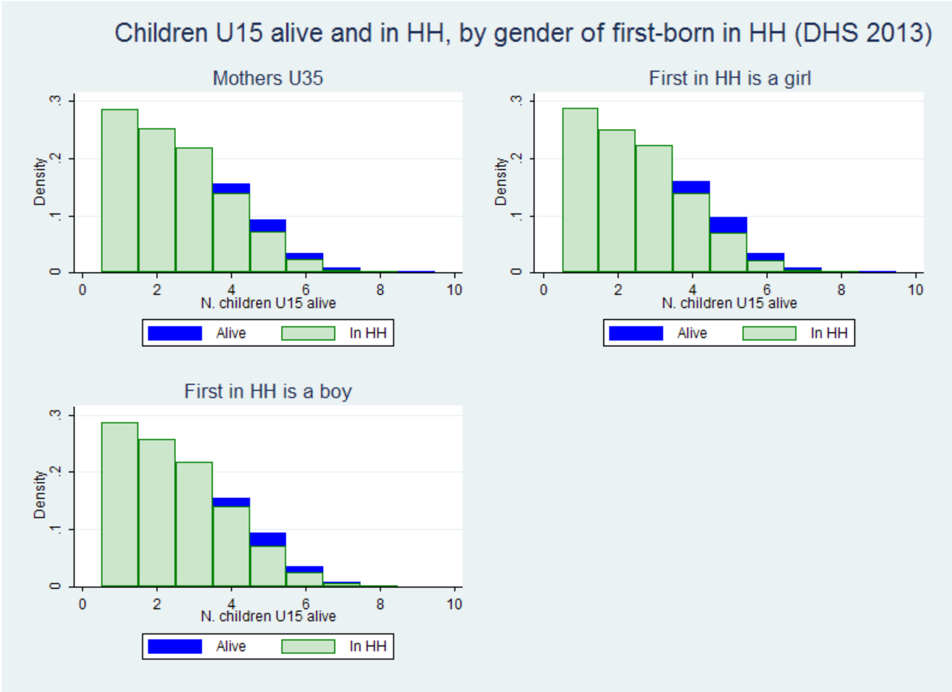
Gender of the first-born child and number of children. Solving the endogeneity of the number of children is based on the exogenous variation in the gender of the first-born. Given that the LSMS-ISA only provide information about children living in the household at the moment of the survey,[30] the gender of the first-born and the actual number of children might be noisily measured, being different from the gender of the first-born still alive and the overall number of living children (not just those still in the household). Analysis of the DHS data suggests this is not the case. First, in the selected sample (households having at least one child under 15 year old at home, mothers under 35 being currently married and living in rural areas) 93.2% of households having a first-born alive who is a girl also have a female first-born residing in the household, the two having a correlation coefficient of 0.85.

Second, there is not much difference between the distributions of children alive or living at home at the moment of the survey, as shown in Figure 4, which compares the information on all children who are alive (in the household or not).[31] That said, there is a statistically significant difference according to the gender of the first-born living in the household, i.e. households with a first-born girl on average have 0.02 more children living outside the household (the average difference between the number of those alive and at home is 0.22). This could reduce the predictive power of the instrumental variable, as households with a first-born girl living at home might have slightly fewer children at home.

The gender of the first-born is as good as random under observable household characteristics, which do not significantly differ according to the gender of the oldest child living at home for the selected sample. Tables A.6 and A.7 show that households whose first child is a boy and those whose first child is a girl differ slightly in terms of observable characteristics when no restriction on mother's age is put on the sample. Small differences also appear when considering the gender of the first ever-born child. However, for the sample of mothers under 35 years old the results confirm that the gender of the first-born is close to random. As the literature on son preference has found (Clark, 2000; Milazzo, 2014; Milazzo, 2012; Jayachandran and Kuziemko, 2011; Banerjee et al., 2014), selective maternal mortality might in part explain those differences, given that households react to the gender of their children, by, for instance, shortening birth-spacing and, thus, increasing the mother's risk of mortality.[33] The DHS data show that the share of mothers with a female first-born falls with mother's age (see also Milazzo (2014)), making it

[30] The post-harvest surveys contain the information on the number of children living elsewhere and their gender, but not on their age. This makes it impossible to use such data for measuring the total number of living children under 15 years of age or for defining the instrumental variable used in this study. Neither is it possible to use it for selecting the sample of interest, given that it is reported only for 513 mothers out of 1266. For those under 45 years old, which could be considered as the age limit for being fertile, the information is available for 551 out of 1838, which is still too small a sample to reach enough statistical power in the first stage regression.
[31] The share of women reporting a lower number of children at home than alive is not negligible: 10.3% of mothers under 35, 8% for those under 30 and 5.2% for those under 25.
[32] The number of children living at home is a subset of the total number of children alive.
[33] Barcellos et al. (2014) show that in India the gender of the *last* child is correlated with household characteristics already for children more than 15 months old.

Figure 4: Number of children U15 alive and at home, by gender of first-born (DHS 2013).[32]



important to select a sample of young mothers to avoid such mortality selection (Figure 5).[34] The decreasing trend concerns all three different types of first-born definitions (ever-born, still alive, living in the household).[35] Cutting the sample at 35 years old solves the selection bias that would come from this mortality pattern.

Generally, any significant difference of household characteristics disappears when limiting the sample to mothers under 35 (Table A.7). Households no longer differ according to the gender of the first-ever born (Panel A), the first-born still alive (Panel B) or the oldest child living at home (Panel C). The point estimates are smaller than for the full sample, meaning that the lack of statistically significant differences is not due to lack of power. The gender of the oldest child living at home can, therefore, be considered as exogenous to household characteristics for the DHS sample of mothers aged below 35. The present study is entirely based on such a sub-sample selected in the LSMS-ISA survey.[36] That said, the LSMS-ISA sample does show a few significant differences, possibly because of its smaller size. Even for the sample of mothers under 35 years old, fathers are 0.07 percentage points less educated and are less likely to be Muslim (second graph in Figure 7). All empirical specifications will therefore control for those characteristics.

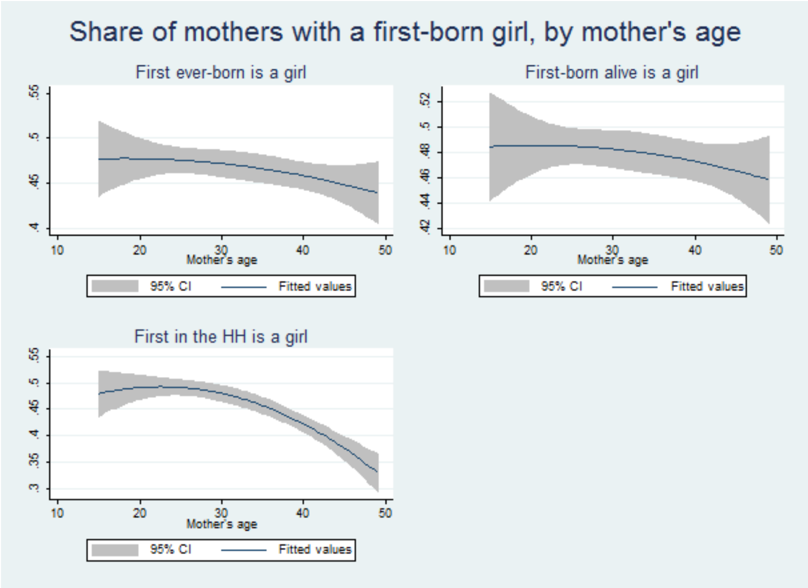
Two other potential threats to identification are differential child mortality between boys and girls and whether households differ along unobservable characteristics. Sex-selective abortion is

[34] An alternative explanation could be that older mothers tend to more easily forget the birth of a girl, than that of a boy. Milazzo (2014) tests for this and finds that the mother's age at first birth is not predictive of the gender of the first-born, hence excluding the possibility of a recall bias.

[35] The curve is steeper in the last case than in the two other cases, probably because girls exit the household to get married, meaning that, overall, there are fewer girls living at home as the mother becomes older.

[36] Overall I select a total of 2.203 households and 2.445 mothers having at least one child under 15, out of which 1.266 are under 35 years old.

Figure 5: Share of mothers with a first-born girl, by mother's age at the moment of the survey (DHS 2013).



not a common practice in rural Nigeria, but parents might devote less resources to girls in early infancy, leading to higher female mortality.[37] The 2008 DHS data indicate that this does not seem to be a major concern as neonatal and child mortality rates are higher for boys, though girls are slightly more likely to die between their first and fifth birthdays.[38] In the 2013 DHS, boys show a slightly higher mortality rate for all categories of mortality (for instance, for under the 5s there are 151 deaths per 1000 births for boys, compared with 137 for girls). I test the probability that the first ever-born died on a dummy equal to one if the first ever-born is a girl for the selected sample and find a statistically significant negative correlation ($\widehat{\beta}$=-0.008, s.e.=0.004), all else being constant.

Weather shocks. Another main threat to the independence assumption is that the gender of the first born could be affected by climate and weather shocks. Given that boys are biologically weaker than girls in utero, households suffering from droughts might be more likely to have a first-born baby girl.[39] Table 1 shows that the gender of the oldest child living at home is orthogonal to weather shocks, either droughts or rainfall. This suggests that the risk of gender

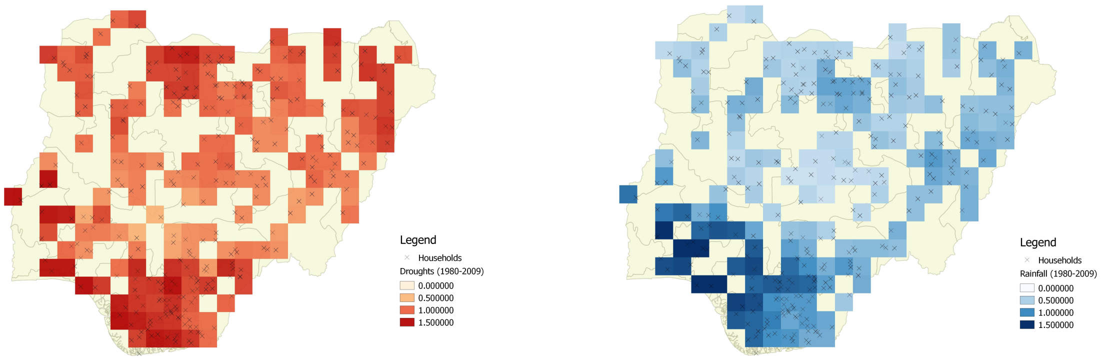
[37] Evidence from India links such differential to the shorter breastfeeding duration experienced by girls (Jayachandran and Kuziemko, 2011).

[38] Neonatal mortality refers to the probability of dying within the first month of life, while child mortality covers the period between birth and the fifth anniversary.

[39] There is still scarce empirical evidence on the selection effect of negative shocks on the gender of the first-born (the effects on children's outcomes have been much better documented). The works by Catalano et al. (2006) and Dagnelie et al. (2014) suggest a worsening of the sex-ratio (respectively, after the 9/11 attack and during the 1997-2004 civil war in DRC), though they suffer from potential selection because of the households' decision to move after those shocks. Hamoudi and Nobles (2014), using data from the United States, find that mothers reporting a conflicting marital situation are 8.8 percentage points less likely to give birth to boys, because of the female survival advantage. However, as noted by Currie and Rossin-Slater (2013), the existing literature has several drawbacks: the aggregation of outcomes at the geographical level misses the changes in population composition if people react to shocks by moving away, the longer the gestation the higher the probability of being affected by a shock, small sample and self-reported measures of stress.

Figure 6: Mean of past climate shocks (1980-2009)

(a) Dry months (b) Rainy months



selection due to climate shocks is limited. Those with a female first child are, if anything, 0.01 percentage points more likely to have benefited from positive shocks between 1980 and 2009.

Weather and climate shocks could still affect the living arrangements by pushing households to have a different composition of children according to the type of shock experienced, by, for instance, fostering boys or girls in or out depending on the shock. Table 2 shows that the numbers of children under 15 and 10 years old are not significantly different across shocks (first Graph in Figure 7). Households benefiting from abundant rainfall are slightly less likely to be polygamous and are less likely to be Muslim, but are a somewhat poorer than those going through a negative weather shock. Therefore, I will control for such factors.[40]

Serial correlation of weather events could represent a further threat to internal validity, making the 2010 shocks not random. The effect of recent shocks could be overestimated if, for instance, places historically affected by droughts are more likely to experience also a drought in 2010. Figure 6 shows that the whole of Nigeria has been affected by droughts and rainfall in the past 30 years (measured as the average number of dry (rainy) seasons over 1980-2009), with some areas having slightly fewer extreme weather events, but still showing a very different pattern than the one in 2010. The different geographical distribution of past shocks with respect to those in 2010 is evident when comparing it with Figure 3.

The lack of serial correlation is also confirmed in Table 2 (columns 2-3). Households having benefited from an above average number of positive climate shocks in the previous 30 years are not more likely to experience a positive weather shock in 2010. In addition, those benefiting from abundant rainfall in 2010 are less likely to suffer from a drought in the same year, given that few have been affected by both shocks (Table 2, column 1).

Even if weather shocks are not serially correlated, it could be that households living in places with an historically higher number of positive or negative climate shocks have developed

[40] The variable of interest of the present study is the number of children under 15 years old and its interaction with the weather shock. A useful check is to compare observable characteristics of households having the same number of children but affected by different shocks. I find the same differences as in Table 2 and Figure 2 (results not shown).

different characteristics to other places, making past climate shocks correlated with local factors. Graphs in Figure 7c look at means-test of households' characteristics averaged at the grid level. Once again, weather shocks appear not to be serially correlated (rainfall in 2010 occurs less in places with an higher historical number of positive climate shocks) and, overall, households do not seem to differ to any considerable extent according to the climate shocks that have occurred in the past. Table 3, though, suggests a precautionary demand for children in places with a historically higher number of droughts, having more children under 15 years old (0.56 pp). The statistically significant difference disappears when looking at all children living at home without any age restriction. This indicates that past climate shocks do not affect the current number of children remaining at home, but only the reproductive behaviour, which is reassuring for this analysis.

4 Main results: Fertility

The first set of results shows the impact of the rainfall shock per se on the number of children dying and living and on fertility preferences.

Estimates with DHS data show that households having benefited from positive rainfall shocks in 2010 report a lower number of children dying by 2013. For each month that rainfall is more than 1 standard deviation above the historical mean, the number of child deaths decreases by -5.13% (Table 4, column 1). This is translated into an increase of 0.6% in the number of survivals, as compared to the mean level (column 2).[41] As a result, the gap between the preferred and actual number of children declines by 1,8% (column 4). Note also that there is no significant reduction in the desired number of children (Column 3), so temporary rainfall shocks do not seem to affect fertility preferences.[42] In contrast, past positive shocks are associated with a lower ideal number of children, in line with the hoarding effect as explained by the theoretical model ($\overline{\phi}$ is here estimated as the mean of positive shocks occurring between 1980 and 2009).

Similar results are found when looking at the LSMS-ISA data (Table 5).[43] For each additional month of rainfall above one standard deviation from the historical mean, the number of child deaths decreases (the magnitude is very similar to that in Column 1, Table 4, though the standard error is larger), while the number of newborns increases (+11.83%, column 2). Hence, good weather shocks have positive effects on fertility for the average household when not taking the initial number of children into account. This is intuitive as the average mother in my sample is young (26.6 years old), and far below her desired number of children, as described in Section 2.2. Droughts do not have any significant impact on child deaths, but only on newborns.

[41] The effect is entirely explained by the sample of young children living at home, which increases by 0.6%

[42] The sample under analysis consist of young mothers under 35, relatively far from the end of their reproductive age, as shown in Section 2.2.

[43] Due to the short time distance between the first and the second wave (6 months), I exclude children born between the first and the second wave, as their conception happened during the 2010 growing season, so potentially preceding the actual weather shock. Similarly, I exclude children that died between the first and the second wave as the date of death is not reported in the data. The attrition rate for the sample of 1.156 rural households with mothers under 35 years old and with at least one child under 15 years old is 1.9% at the household level and 2.6% at the individual level and not correlated with the weather shocks.

The higher mortality and fertility reported in areas that have historically been suffering from droughts (columns 3-4) indicate a precautionary demand for children. Similarly, places having benefited from more abundant rainfall in the previous thirty years show a lower fertility, in line with the hoarding hypothesis (column 2).

The average health status of children deteriorates after a temporary positive shock. Table 6 shows that the average Weight-for-Height decreases by almost 0.1 s.d. In addition, the number of vaccinated children decreases. This is at odds with the traditional literature on the demographic transition that sees a falling mortality rate as the main driver for investments in human capital, inducing a substitution between child quantity and quality (Angeles, 2010). While such mechanism might be true in the longer term, in the short term lower mortality appears to be associated with a higher number of surviving children, pushing parents to decrease the investment in children.[44] As the results in Section 5 will show, it might be that parents are diverting the resources allocated to children away from vaccinating them towards feeding them.

That said, Table 7 shows that positive shocks did, in particular, worsen the health conditions of those children already born at the time of the shock and who were 2 years old (a deterioration in all 3 anthropometric outcomes). There is, on the contrary, no significant impact on those that were in utero. Moreover, those conceived after the shock do, in fact, have significantly higher height for age and weight for age outcomes. Overall, these results suggest that the larger number of newborns due to the positive shock led to increased competition for resources to the detriment of the older siblings.

First-stage results. The theoretical framework shows that the fertility adjustment positively depends on the initial number of children. Large households might be more at risk of child mortality, and hence benefit more from its reduction. In addition, they are closer to their ideal family size, so their fertility adjustment should be larger than for small households. I exploit this prediction by introducing an interaction effect between the initial number of children and the weather shock.

The number of children aged under 15 is measured in the pre-harvest survey of 2010, immediately after the shock, and is instrumented by the gender of the oldest child living in the household and its interaction with the weather shock.[45] The first-stage regression shows that households with a female first-born have on average 0.27 more children aged below 15 (Table 9, columns 1 and 3[46]). The excluded instruments have a good predictive power (see the

[44] The children are too young to make parents reduce education expenditures.

[45] The number of children is standardised by subtracting one from the actual number of children. Given that in the sample the minimum number is one, this standardisation allows us to interpret the estimated coefficient of Rain_{2020} as the impact of the weather shock for households with only one child. As a consequence, the interaction must be interpreted by multiplying the estimated coefficient by a certain number of children minus one. For instance, if we consider the average number of three children we must then multiply the interaction coefficient by two.

[46] Columns 3 and 4 provide the first-stage results for the food security regression, which controls for food security in 2011.

Angrist-Pischke tests reported in Table 10).[47]

Second stage results. The results from the second stage of the 2SLS estimator are in line with the fourth prediction of the model. The more children parents have at the time of the shock and the the larger the positive shock is, the less newborns they will have.

Table 10, column 1, shows that for a household with the average number of three young children, mortality declines by -0.013 (0.323-0.336) for every additional month of positive rainfall shock.[48] The decline is larger the more living children there are: the decrease is of -0.18 for a household with four children and -0.35 for those with five children, whereas it is not statistically significant for households with less than three children.

Column 2 shows that one month of positive rainfall shock increases the number of newborns by 0.42 for households with only one child (the minimum number in the selected sample), as compared with the counterfactual. The increase is smaller the higher the number of children in the household at the moment of the shock. For a household with the average number of three, the increase is only 0.046. Households with more than three children reduce their fertility as compared to those not benefiting from abundant rainfall (-0.14 for those with four and -0.32 for those with five children).

Adjusting fertility behaviour to positive weather shocks could be explained by the negative effect of the same shock on child mortality. The more young children there are, the more a household benefits from a reduction in child mortality in times of abundant rainfall (Column 1). Yet, given the transitory nature of positive shocks, the children that have survived still have a non-zero probability of dying. The parents continue to have a non-null number of newborns, which is expected given the relatively young age of the mothers and the fact that, on average, the number of children is still far below the ideal number (see Section 2.2).[49]

It is interesting to notice that the adjustment is much larger for households with more than three children, which constitute one third of the sample. They are also the ones who are closest to their desired number. Indeed, the DHS data show that those closest to their preferred number, for which the difference preferred-actual is less than three, are those who already have 3.5 children on average, corresponding to one-fourth of the DHS sample. This is in line with the

[47] Table 8 shows the first-stage regression by gradually adding different groups of controls. While the gender of the first-born is not per se significantly correlated with the number of young children, the estimated coefficient becomes statistically significant when we condition on parents' characteristics. In particular, mother's education plays an important role, for the son-preference effect is the strongest among the least educated. Adding further controls increases the magnitude and precision of the coefficient (especially the age of the first-born).

[48] The reduction of child mortality could be due to the increased harvest production and income occurring in the very short-term thanks to the rainfall shock, as shown in Table A.8. This is in line with results found by Baird et al. (2007). In turn, extreme rainfall might be detrimental. For instance, Kudamatsu et al. (2012) consider large quantities of precipitations combined with high temperature to define malaria-propitious environments and find that being exposed to extreme conditions (6 months of malaria-type weather conditions) increases infant mortality. This is not in contradiction with my results, given that their weather conditions would correspond here to extreme floods, which I exclude because they are, clearly, not positive weather shocks.

[49] An alternative mechanism that could explain the decrease in the number of newborns is that parents stop being altruistic when the survival probability increases and their utility function does not increase any more with the number of children. But it is not clear why only large households should change their preferences and not small households.

theoretical model, for which the lower the distance to the preferred size, the lower the number of newborns and, hence, the larger the adjustment.

The decline in fertility experienced by large households could be also in line with the hoarding hypothesis, given that thanks to the positive shock there is no need to replace the hoard of children they already have. As shown in Table 4, the distance to the preferred number of children decreases thanks to the shock, meaning that households might be also revising their fertility target downward.

Droughts do not appear to affect household fertility behaviour. Weather shocks in 2010 for the selected sample were mainly positive ones, while droughts only concerned around 45% of the sample and lasted on average 3 weeks. Probably because of this, the instrumental variables used in the regressions looking at the effect of droughts have low predictive power, as reported in columns 3-4. Considering weather shocks in 2011 (results not shown), which was a much drier year than 2010 (all households got at least one month of drought, as compared to only 45% in 2010), each additional month of drought increases child mortality by 0.005 (p-value 0.035), but the effect is not robust to the inclusion of the interaction Children*Drought$_{2011}$. The number of newborns increases by 0.018 (p-value 0.02) for each additional month of drought but the effect is not statistically significant when all the controls are included.

Historical shocks. While there is no clear identification of the impact of historical shocks, the correlation between past positive shocks, child mortality and newborns is nevertheless illustrative. Places having benefited from a large number of good seasons in the previous thirty years have a lower, but not significant, child mortality (-0.08, Table 10 column 1) and, interestingly, show significantly fewer newborns (column 2, -0.17),[50] in line with the hoarding effect and the last model prediction.

Parallel estimates with the 2013 DHS data, which have more power thanks to the larger sample size, confirm that a long-term exposure to positive climate shocks is associated with a lower number of dead children (Table A.9). A further support of the precautionary demand result is the fact that in places with historically good climate shocks the mother's age at first birth (DHS data) is higher for the whole sample of mothers (results not shown). This is in line with the theoretical prediction developed by Doepke (2005), who explains this result with the lower uncertainty about the number of surviving children in such environments, making it possible to delay fertility.[51]

In conclusion, the model predictions 1-4 are supported by the empirical results, showing that the fertility adjustment is larger the more living children there are at the time of the shock.

[50] Places having historically been affected by droughts might have a precautionary demand for children, as suggested by the positive estimated coefficients (though not statistically significant) on the number of child deaths and newborns (columns 3, 4).

[51] Although, clearly, other mechanisms might explain this positive correlation. For instance, places with a larger number of positive climate shocks might be richer, leading to women accessing higher education and delaying their fertility.

5 Implications for food security

The results in the previous section showed that, for the average household in the sample, positive weather shocks increase fertility, meaning that households are larger than before and, in particular, have more dependent members, i.e. more young children. The theoretical model also predicts that parents might decrease their own consumption given the increased number of children.

To investigate the fourth theoretical prediction, I look at food security variation between the 2011 and 2013 post-harvest periods. The hunger scale measuring food security is not sensitive to household size, nor to the number of children, provided that the sample is composed of households with at least one child. Still, it contains an item that is particularly useful, which considers whether adults reduce their food consumption in order to buffer young children (see Section 2). A decrease of food security along this dimension for households having benefited from abundant rainfall in 2010 would then imply that a higher number of surviving children makes households more vulnerable and less food secure.

In order to explore this hypothesis, I look at the variation in household food security in the year following the positive shock and two years after. Table 11 shows the change in food security between the pre-harvest and post-harvest season, corresponding to September 2010 and March 2011, respectively. The overall score in column 1 shows an increase of 0.34 standard deviations of food security thanks to one additional month of positive weather conditions. This does not depend on the number of children (the interaction term is insignificant). In terms of single items, positive weather shocks mainly make households rely less on the least preferred food (column 2) and slightly improve food diversity (column 3).

The results two years later are remarkably different. Table 12 reports the variation in food security between two post-harvest seasons, those in 2011 and 2013. On average, the 2010 weather shock still makes households 0.03 s.d. more food secure three years later. However, having a larger number of young children living at home fades away such positive effect. For an average household with three children, and after controlling for the food security level in 2011, an additional month of positive rainfall shock in 2010 increases food security by 0.028 s.d. (column 1), but the effect turns negative for households with four (-0.49 s.d.) and five (-0.99 s.d.) children.[52]

The negative effect of the interaction term is mainly explained by a deterioration of the first and fifth items, Table 13.[53] The former captures food quality, meaning that households rely more on less preferred food. The latter, on the contrary, indicates that adults restrict their consumption to buffer young children. This also confirms the last prediction of the model: parents

[52] OLS estimates show different results, with large families being 0.045 standard deviations less food secure (see the bottom of Tables 12 and 13). This negative correlation disappears when fertility is instrumented, as is very often the case in the literature addressing the endogeneity of fertility (see, for instance, Angrist et al. (2005)). The negative effect of high fertility appears to be slightly mitigated by positive weather shocks, resulting in a decrease of food security of -0.036 s.d. instead of 0.045 (column 1). It is rather small households benefiting from abundant rainfall that increases their food security by 0.038 s.d.

[53] The single items are not standardised because they are categorical variables going from 0 to maximum 7.

decrease their own consumption, given the larger number of children living in the household. In contrast, an opposite but much smaller coefficient is found for item 7, which measures food availability at home.

The fact that households cut adult food consumption for the benefit of children is in line with the fertility adjustment results and can be explained by the theoretical model. Large households that decrease their fertility still end up with more surviving children thanks to the fall in mortality. As a consequence, there is less food available and adults decrease their own consumption to buffer young children. Small households, on the contrary, continue to have a non-null number of newborns, but, because they have benefited very little from the mortality decline, their household size has probably changed very little, without any negative implications for their food security status.

6 Robustness Checks

This section provides robustness checks concerning the sample selection and the validity of the instrumental variable. With regard to the sample, I test the robustness of the results for the inclusion of non-biological children under 15 years old living in the household. Then, with regard to the instrument validity, I exploit the DHS 2013 data to estimate the mortality and fertility regressions and run the first-stage regression using different definitions of first-born child (ever-born, alive and living in the household). Finally, I estimate the first-stage regression excluding the children's gender ratio and show that the instrument still has good predictive power.

The first stage in Table 9 has shown that son preference makes households have, on average, 0.27 more young biological children when the first-born is a girl. In the main analysis, the sample was restricted to the number of children living in the same household with their two biological parents. However, Nigerian households sometimes also include other young children who do not have their own biological parents living with them in the household. The first check consists in including all those other children (nephews, nieces, stepchildren and adopted children, grandchildren of the household head) aged below 15 living in the household at the moment of the survey in addition to the biological ones and taking into account their overall number.

Table A.11 shows that the gender of the first-born is still significantly correlated with the number of children under 15 and the estimated coefficient is even slightly larger in magnitude (0.36 instead of 0.27). However, the effect of an additional child on food security is lower in this case (0.17 instead of 0.25), which might suggest that own biological children affect more household food security more than any other young child living at home.

The main robustness check consists in replicating the mortality and fertility results with the DHS 2013 dataset. The issue of potential noise in the measurement of the first-born gender and the number of living children is less of a concern in this dataset, which tracks the whole birth history of each sampled woman. I retrospectively determine the number of children living in the household at the moment of the 2010 shock, by adding those who died afterwards and subtracting those born afterwards. Similarly, I reconstruct mother's age by looking at their date of birth and considering their age in February 2010, the first month of the growing season. As for the main estimates, I select rural households with mothers under 35 years old at the time of the shock and with at least one child under 15 years old at home. The instrumental variables used are the gender of the first-born living in the household and its interaction with the shock.

Table A.12 remarkably shows the same effects as for the main specification for both the mortality and fertility regressions. For households with the average number of three young living children, one additional month of rainfall decreases child mortality by 0.027 and increases fertility by 0.051. However, households with only one child in 2010 appear to suffer from an increase in child mortality of 0.37 for each additional month of abundant rainfall and to increase their fertility by 0.61. Compared whit the estimated coefficient presented in Table 10, the standard error is smaller and the magnitude of the estimated coefficient is larger. A possible explanation could be that positive weather shocks increase the spreading of malaria, increasing child mortality, as found by Kudamatsu et al. (2012), though I cannot provide any evidence in support of this. A caveat concerns the low predictive power of the instruments for the first-stage regression for the number of children U15 regressor.

Another way of testing the robustness of the instrument is by running the first-stage with the Nigeria 2013 DHS data, by applying the same selection criteria to the sample (households with both parents alive, mothers under 35 years old, living in rural areas, with at least one child under 15 years old) . The information reported there is useful for checking the magnitude of the son-preference effect on fertility, considering the ever-born children, those actually alive at the moment of the survey and those living in the household. Table A.13 shows that households with a first ever-born girl have on average 0.11 more ever-born children. This is very much in line with the result found by Milazzo (2014) who shows that having a first ever-born girl is associated with 0.11 more children for mothers between 30 and 49 years old.[54] However, column 2 shows that the instrument is not robust to the inclusion of its interaction with the weather shock.

The magnitude of the son-preference effect on fertility is larger when looking at the number of children under 15 years old who are alive at the moment of the survey (columns 3 and 4), suggesting that it is the gender of the first surviving child that matters the most for son-preference related behaviour. Households with a female first-born still alive have, on average, 0.15 more children. The magnitude is lower than that found with the LSMS-ISA data (0.27). In this specification, the instrument is robust to the inclusion of the interaction with the rainfall shock. Columns 5 and 6 report the closest specification to the one used with the LSMS-ISA, as shown in Table 9. There are on average 0.11 more young children in those households with a female first-born still living in the household. The magnitude is slightly lower than that found with the LSMS-ISA data. It is reassuring to see that the instrument is robust to the inclusion of the interaction with the weather shock (column 6).

To interpret the interaction effect of the number of children with the rainfall shock as causal, an important assumption is that the instrument is not correlated with the error term. That is to say, that the rainfall shock for those having had a girl (which is the second instrumental variable) does not affect preferences. While I cannot completely rule out the absence of such correlation, there is some evidence that suggests this is not the case. First, results in Table 4 (column 4) show that the 2010 rainfall shocks have not significantly changed the ideal number of children parents would like to have. Second, the rainfall shock could represent an income shock and might affect fertility preferences through this channel. Given that I control for the rainfall shock in all specifications, this should not be a problem. The concern would be if the shock affects preferences in a different way according to the gender of the first-born. To check this, I run the main specification with two modifications. The number of children is interacted with the harvest value (instead of rainfall) and, in addition to the two usual instrumental variables, I add rainfall as a third. The strength of the first stage is confirmed. The second stage does not

[54] Her specification is, however, different from the one used in this study. She looks at 2008 DHS data, including urban and rural households (sample of 17589 observations), controlling in addition for mother's group age fixed effects, birth year fixed effects, as well as ethnic and region-specific time trends.

show any significant effect of either harvest value or its interaction with the stock of children on the number of newborns (results not shown). These two pieces of evidence tend to exclude a change in preferences caused by the rainfall shock.

As shown in Table 8, controlling for mother's and household's characteristics is important for the strength of the instrumental variable. In particular, mother's education and the z-score of the gender-ratio play an important role. While I cannot substitute mother's education with any other proxy, the gender-ratio captures gender productivity differentials that can, at least in part, be proxied by the age of the first-born. Table A.14 reports the first-stage regression excluding the gender-ratio z-score. The instrument is still highly significant, the estimated standard errors are even slightly lower and the F-test statistics show that the instrumental variable is even stronger than in Table 8. The magnitude is slightly lower, being 0.20 instead of 0.27. This confirms that the strength of the instrumental variable is not driven by the children's gender-ratio.

Finally, the negative impact of a large number of children on household food security could be just a regression to the mean. After the initial positive effect of rainfall, households could simply go back to the initial level, hence showing a negative trend. Two main points argue against this interpretation. First, the negative effect is still there even when looking only at the impact on the level of food security in 2013. Second, Table A.15 shows that even when controlling for the most recent shocks, which occurred in 2012, the effect of the 2010 ones is still present.

Conclusion

This paper investigates household fertility decisions in a context of high child mortality and looks at the implications in terms of household food security in rural Nigeria. While it is plausible that a fall in child mortality might reduce fertility rates, empirical evidence on long-term effects remains mixed, while on short-term impacts it is totally absent. This study tests the short-term reaction of household fertility to an exogenous decline in child mortality resulting from positive rainfall shocks.

By exploiting a unique household panel dataset, I find that abundant rainfall reduces child mortality. In particular, it is large households with more than two living children at the moment of the shock that benefit the most from the increase in child survival. Thanks to the shock, the larger number of surviving children brings parents closer to their desired number. Households respond by reducing their fertility, but not completely, leading to an imperfect adjustment. Only those with more than three children considerably decrease their fertility (-0.18 newborns for those with four and -0.35 for those with five children). Conversely, the smaller households (with the average number of three children) increase their fertility by 0.046 more newborns for each additional month of positive rainfall shock. Given the transitory nature of such shocks, those children that have survived still have a non-zero probability of dying and parents continue to have a non-null number of newborns, which is expected given the relatively young age of the mothers and the fact that, on average, the number of children is still far below the preferred number. The empirical results provide support for the theoretical framework proposed in the paper.

The paper further explores the implications in terms of household welfare, focusing on food security. In line with an imperfect adjustment and an increased number of children, household food security declines. In particular, I find that parents choose to allocate more resources to their children, by cutting down on their own food consumption to buffer their children's.

These results have important implications for the design of programs aiming to reduce fertility in developing countries. First, they show that fertility behaviour is a dimension along which households adjust to positive temporary shocks and that this adjustment can have negative implications for household welfare. Second, policy makers designing family planning programs in high child mortality contexts should consider household precautionary demand for children. Interventions aimed directly at reducing fertility have often seemed to fail. They may be more successful in places where child mortality is not such constraint and where parents do not need a stock of children. For future research evaluating the costs and benefits of interventions aiming at reducing child mortality it would be important to consider the effects on the fertility behaviour as well.

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Table 1: Balance of households' characteristics according to the gender of the first-born

	(1) Drought 2010	(2) Rain 2010	(3) Mean Drought (1980-2009)	(4) Mean Rain (1980-2009)	(5) N. children U15	(6) N. children U10
First-born is a boy	0.00442	1.001	0.939	0.410	3.552	2.141
	(0.00702)	(0.00491)	(0.00270)	(0.00200)	(0.00978)	(0.0112)
First-born is a girl	-0.0238	0.992	0.944	0.425	3.591	2.237
	(0.0375)	(0.0266)	(0.0111)	(0.00531)	(0.0670)	(0.0591)
Diff.	-0.0282	-0.00939	0.00487	0.0147*	0.0398	0.0957
	(0.0445)	(0.0315)	(0.0139)	(0.00768)	(0.0770)	(0.0704)
N	1352	1352	1352	1352	1356	1354

Agro-ecological zone fixed effects. Standard errors in parentheses clustered at the grid level and Agro-ecological level

Table 2: Balance of households' characteristics having the rainfall shock

	(1) Drought 2010	(2) Mean Drought (1980-2009)	(3) Mean Rain (1980-2009)	(4) N. children U15	(5) N. children U10
No rain 2010	0.259	0.485	0.188	3.627	2.170
	(0.0695)	(0.0762)	(0.0395)	(0.0471)	(0.0413)
Rain 2010	-4.65e-14	0.412	0.156	3.558	2.156
	(4.65e-14)	(5.43e-14)	(3.90e-14)	(3.63e-13)	(3.93e-13)
Diff.	-0.259***	-0.0725	-0.0313	-0.0696	-0.0131
	(0.0695)	(0.0762)	(0.0395)	(0.0471)	(0.0413)
N	1352	1352	1352	1352	1350

Agro-ecological zone fixed effects. Standard errors in parentheses clustered at the grid and Agro-ecological level

Table 3: Balance checks of household characteristics averaged at the grid-level, by past climate shocks (1980-2009).

	(1) N. children U15	(2) N. children	(3) First-born is a girl
More droughts (1980-2009)	3.325	4.118	0.388
	(0.0634)	(0.0730)	(0.0167)
More rainfall (1980-2009)	2.763	4.075	0.446
	(0.166)	(0.329)	(0.0375)
Diff. (drought vs rainfall)	0.562***	0.0422	-0.0572
	(0.177)	(0.337)	(0.0410)
N	1347	1347	1347

"More droughts/rainfall (1980-2009)" is a dummy equal to one if the average of dry (rainy) months occurred between 1980 and 2009 included is higher than the average of rainy (dry) months occurred in the same time period. Standard errors in parentheses clustered at the GPS level

Table 4: OLS. Positive weather shocks affecting the number of newborns, dead children, children alive and gap between ideal and actual offspring size. 2013 DHS

	(1) **N. children died**	(2) **N. children alive**	(3) **Ideal number of children**	(4) **Ideal-Actual**
Rain_{2010}	-0.00361***	0.0172*	-0.0772	-0.0854*
	(0.00131)	(0.0102)	(0.0648)	(0.0486)
Mean $\text{Rain}_{1980-2009}$	-0.0245***	-0.0981	-0.437***	-0.330***
	(0.00183)	(0.112)	(0.125)	(0.114)
Controls	Yes	Yes	Yes	Yes
Agro-eco. zone FE	Yes	Yes	Yes	Yes
N	6320	6320	5773	5773
Dep. var. mean	0.0703	2.841	7.591	4.770
r2	0.0155	0.447	0.303	0.287

Additional controls: Mother's rank, age, education, father's education, wealth index, dummy for Muslim, set of dummies for ethnic groups, z-score for gender ratio, age of first-born. Agro-ecological area fixed effects. Standard errors in parentheses clustered at the Agro-ecological area.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: OLS. Negative and positive climate shocks in 2010 affecting number of newborn and dead children in 2012. LSMS-ISA

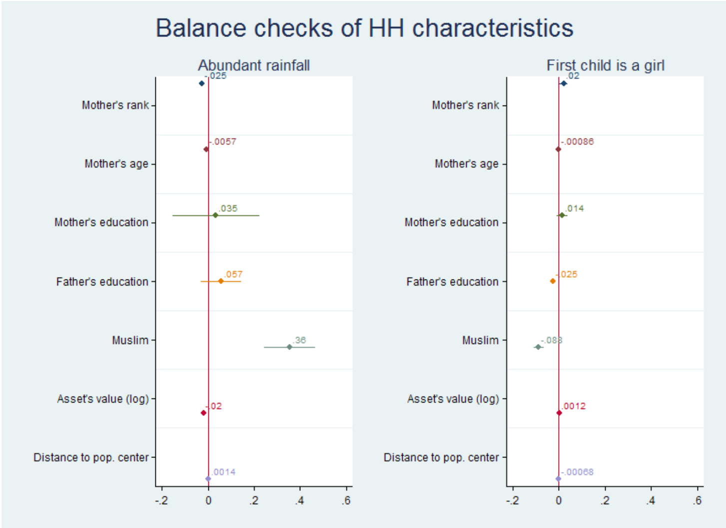
	(1) **N. children dead**	(2) **Newborn**	(3) **N. children dead**	(4) **Newborn**
Rain_{2010}	-0.00511	0.0393***		
	(0.00395)	(0.0117)		
Mean $\text{Rain}_{1980-2009}$	-0.0839	-0.141***		
	(0.0748)	(0.0289)		
Drought_{2010}			-0.00317	-0.0837***
			(0.00867)	(0.00550)
Mean $\text{Drought}_{1980-2009}$			0.0470***	0.0834**
			(0.0165)	(0.0380)
Controls	Yes	Yes	Yes	Yes
Agro-eco. zone FE	Yes	Yes	Yes	Yes
N	1251	1251	1251	1251
Dep. var. mean	0.0671	0.332	0.0671	0.332
r2	0.0347	0.0531	0.0321	0.0543

Additional controls: mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, distance in km from population center, age of the first-born, set of dummies for ethnic groups, z-score of gender ratio of children under 15 and its interaction with the climate shock; Agro-climatic zone fixed effects. Standard errors clustered at grid level and agro-climatic zone in parentheses. Sample weights applied.

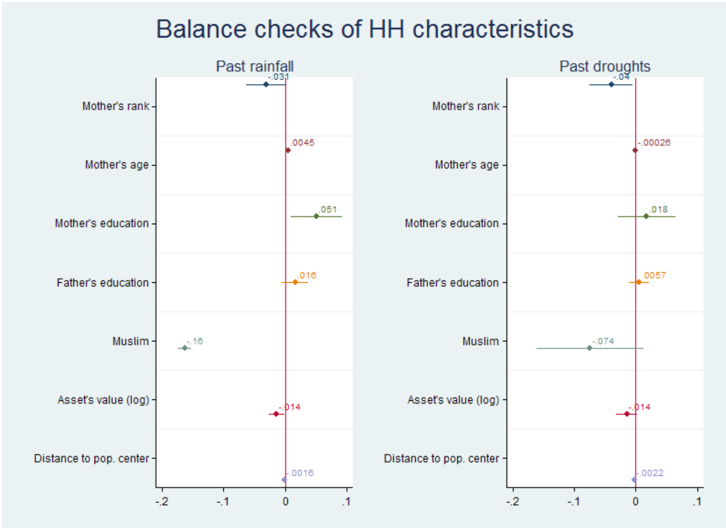
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 7: Balance checks of household characteristics.

(a) By 2010 shock and the gender of the first-born.



(b) By past climate shocks (1980-2009)



(c) Characteristics at the grid-level, by past climate shocks (1980-2009)

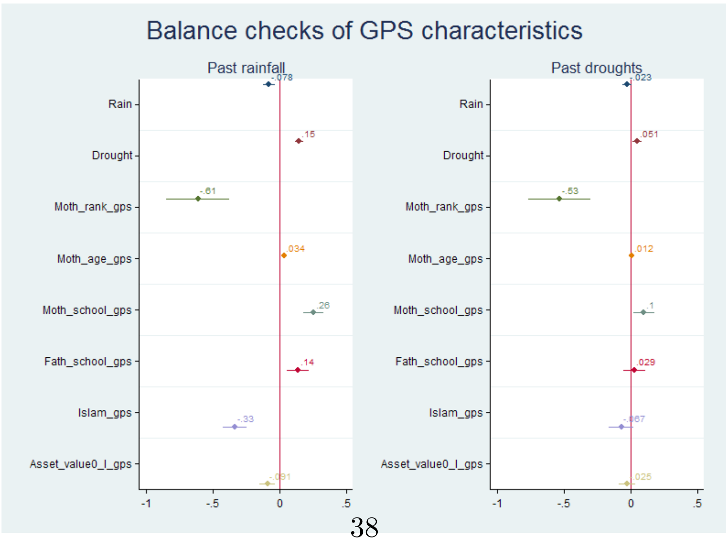


Table 6: OLS. Effects of positive weather shocks on anthropometrics of all children U5 and vaccination of children born after the 2010 weather shocks. 2013 DHS

	(1) **WFH z-score**	(2) **HFA z-score**	(3) **WFA z-score**	(4) **N. children vaccinated**
Rain_{2010}	-0.0988***	0.00122	0.000528	-0.0857***
	(0.0381)	(0.0205)	(0.0288)	(0.0217)
Mother's height	-0.00286*	0.0404***	0.0231***	-0.00315
	(0.00150)	(0.00194)	(0.00108)	(0.00328)
Mean $\text{Rain}_{1980-2009}$	-0.388**	0.549**	0.0722***	-0.377***
	(0.196)	(0.266)	(0.0270)	(0.115)
Controls	Yes	Yes	Yes	Yes
Ag-eco. zone FE	Yes	Yes	Yes	Yes
N	7997	7958	8468	3738
Dep. var. mean	-0.647	-1.501	-1.491	0.776
r2	0.0141	0.0824	0.106	0.0368

Agro-ecological area fixed effects. Standard errors in parentheses clustered at the Agro-ecological area. Controls: Mother's rank, age, education, father's education, wealth index, dummy for Muslim, set of dummies for ethnic groups, z-score of gender ratio, age of first-born.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: OLS. Effects of positive weather shocks on children's anthropometrics in 2013, by moment of exposure to the shock. Children aged 0-5 at the moment of the survey (2013 DHS).

	Already born during the shock			**In utero during the shock**			**Born more than 9 months after the shock**		
	(1) **WFH z-score**	(2) **HFA z-score**	(3) **WFA z-score**	(4) **WFH z-score**	(5) **HFA z-score**	(6) **WFA z-score**	(7) **WFH z-score**	(8) **HFA z-score**	(9) **WFA z-score**
Rain_{2010}	-0.0809***	-0.0456***	-0.0617***	-0.0824	-0.0264	-0.00440	-0.109***	0.0603**	0.0619**
	(0.0235)	(0.0137)	(0.00501)	(0.0569)	(0.0214)	(0.0420)	(0.0346)	(0.0250)	(0.0303)
Mother's height	-0.0133***	0.0548***	0.0245***	0.0126***	0.0418***	0.0183***	-0.00372	0.0345***	0.0261***
	(0.00215)	(0.00196)	(0.000883)	(0.00430)	(0.00566)	(0.00519)	(0.00293)	(0.00148)	(0.00271)
N	2489	2469	2566	1617	1630	1722	3551	3522	3824
Dep. var. mean	-0.393	-1.868	-1.517	-0.517	-2.040	-1.689	-0.906	-0.943	-1.376
r2	0.0172	0.115	0.105	0.0245	0.120	0.140	0.0222	0.0696	0.100

Agro-ecological area fixed effects. Standard errors in parentheses clustered at the agro-ecological area. Controls: average number of positive shocks 1980-2009, Mother's rank, age, education, father's education, wealth index, dummy for Muslim, set of dummies for ethnic groups, z-score of gender ratio

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: First stage, positive weather shock.

Dep. var.: N. children U15	(1)	(2)	(3)	(4)	(5)	(6)	(7)
First born is a girl	0.0397	0.0398	0.120**	0.245**	0.288***	0.291***	0.271***
	(0.0897)	(0.0891)	(0.0346)	(0.0458)	(0.0242)	(0.0253)	(0.0408)
First-born*Rain$_{2010}$						0.0196	
						(0.0188)	
Rain$_{2010}$						0.0000210	
						(0.00979)	
Parents controls	No	No	Yes	Yes	Yes	Yes	Yes
Household controls	No	No	No	Yes	Yes	Yes	Yes
Age of first-born	No	No	No	No	Yes	Yes	Yes
Ethnic groups dummies	No	No	No	No	No	Yes	Yes
Agro-eco. zone FE	No	Yes	Yes	Yes	Yes	Yes	Yes
N	1356	1356	1286	1277	1277	1277	1277
Dep. var. mean	1.935	1.935	1.952	1.953	1.953	1.953	1.953
N. clusters	163	163	163	162	162	162	162
Instrument F-test	0.196	0.200	12.06	28.54	141.6	132.0	112.7

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the Rain$_{2010}$ coefficient for households with the minimum number of young children, one. Parents controls: mothers' rank, education, age and age squared, father's education; Household controls: total value of assets, dummy for Muslim, distance in km from population center, z-score of gender ratio of children under 15 and its interaction with the climate shock; Agro-ecological zone fixed effects. Standard errors clustered at grid level and Agro-ecological zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: First stage, positive weather shock.

	(1) N. children U15	(2) Children*Rain$_{2010}$	(3) N. children U15	(4) Children*Rain$_{2010}$
First born is a girl	0.272***	0.0322	0.267***	0.0212
	(0.0334)	(0.0479)	(0.0368)	(0.0470)
First-born*Rain$_{2010}$	0.0188	0.223***	0.0189	0.229***
	(0.0151)	(0.0170)	(0.0162)	(0.0168)
Rain$_{2010}$	0.00308	-0.00758	0.00112	-0.00449
	(0.0116)	(0.0355)	(0.0128)	(0.0357)
Mother's rank	-0.392***	-0.516*	-0.394***	-0.520*
	(0.0384)	(0.189)	(0.0384)	(0.192)
Mother's age	0.339**	0.658***	0.349**	0.665***
	(0.0869)	(0.0766)	(0.0846)	(0.0688)
Mother's age sqd	-0.00555**	-0.0112***	-0.00573**	-0.0113***
	(0.00163)	(0.00128)	(0.00159)	(0.00118)
Mother's education	-0.167***	-0.0940	-0.172***	-0.104
	(0.0247)	(0.0445)	(0.0232)	(0.0465)
Father's education	0.109	0.0926*	0.113	0.0966**
	(0.0544)	(0.0320)	(0.0528)	(0.0301)
Muslim	0.200	0.260	0.203	0.255
	(0.107)	(0.210)	(0.111)	(0.217)
Asset's value (log)	-0.0213	-0.0279	-0.0150	-0.0239
	(0.0241)	(0.0364)	(0.0246)	(0.0353)
First-born age	0.133***	0.118*	0.132***	0.117*
	(0.00900)	(0.0398)	(0.00884)	(0.0405)
Gender ratio (z-score)	-0.115**	0.0725***	-0.113**	0.0715***
	(0.0339)	(0.00692)	(0.0354)	(0.00692)
Gender ratio (z-score)*Rain$_{2010}$	0.000473	-0.172***	-0.000916	-0.172***
	(0.0151)	(0.0132)	(0.0158)	(0.0135)
Distance to pop. center	0.000697	-0.00326*	0.000811	-0.00312
	(0.000734)	(0.00105)	(0.000880)	(0.00139)
Hausa-fulani	0.0368	0.0569***	0.0368	0.0599***
	(0.0721)	(0.0012)	(0.0709)	(0.00380)
Igbo	0.314*	0.178	0.290	0.162
	(0.122)	(0.0942)	(0.126)	(0.101)
Yoruba	0.301	0.122	0.282	0.111
	(0.296)	(0.189)	(0.302)	(0.197)
Mean Rain$_{1980-2009}$	-0.225	-0.189	-0.223	-0.186
	(0.405)	(0.274)	(0.411)	(0.266)
Food security 2011			-0.0411**	-0.0303
			(0.00777)	(0.0200)
Constant	-5.672**	-9.526***	-5.870***	-9.664***
	(0.994)	(1.000)	(0.958)	(0.851)
N	1277	1277	1255	1255
Dep. var. mean	1.953	2.052	1.955	2.056
N. clusters	162	162	162	162
Agro-ecological zone FE	Yes	Yes	Yes	Yes

The number of children U15 is standardised as n. children U15 - 1, so as to make the interpretation of the Rain$_{2010}$ coefficient for households with the minimum number of young children, one. Controls: mothers' rank=order of mothers in the same household (equal to 1 in monogamous households, higher for polygamous ones), mothers and fathers education=categorical variable equal to 0 if never attended a formal school, to 1 if attended at least primary, to 2 if attended secondary, to 3 if higher than secondary, age and age squared=mother's age at the moment of the survey and its squared term, total value of assets=sum of declared values for all the assets owned, dummy for Muslim=equal to 1 if household is Muslim and zero if Christian (omitted variable is traditional religion), distance in km from population center=kilometres from the nearest town of more than 20.000 inhabitants, age of first-born, z-score of gender ratio of children under 15 and its interaction with the climate shock=z-score of the ratio of the number of sons over daughters under 15 years old (equal to zero if there is only one child); Agro-ecological zone fixed effects. Standard errors clustered at grid level and Agro-ecological zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: 2SLS. Negative and positive climate shocks in 2010 affecting number of newborn and dead children in 2012.

	(1) N. dead children	(2) Newborns	(3) N. children dead	(4) Newborns
N. children U15	0.142	0.243*	0.0326	0.0702*
	(0.131)	(0.141)	(0.0364)	(0.0417)
Children*Rain$_{2010}$	-0.168*	-0.187**		
	(0.0956)	(0.0932)		
Rain$_{2010}$	0.323	0.420**		
	(0.197)	(0.189)		
Mean Rain$_{1980-2009}$	-0.0780	-0.168***		
	(0.0672)	(0.0431)		
Children*Drought$_{2010}$			-0.0439	0.00603
			(0.0433)	(0.0634)
Drought$_{2010}$			0.0744	-0.0530
			(0.0869)	(0.123)
Mean Drought$_{1980-2009}$			0.0225	0.0513
			(0.0482)	(0.0496)
Controls	Yes	Yes	Yes	Yes
Agr-ecological zone FE	Yes	Yes	Yes	Yes
N	1266	1266	1266	1266
Dep. var. mean	0.0504	0.290	0.0504	0.290
AP F-test (1)	64.62	64.62	10907.8	10907.8
p-value	0.00402	0.00402	0.00000194	0.00000194
AP F-test (2)	182.9	182.9	6.243	6.243
p-value	0.000874	0.000874	0.0878	0.0878

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the Rain$_{2010}$ coefficient for households with the minimum number of young children, one. See notes in Table 9. Controls: mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, distance in km from population center, age of first-born, set of dummies for ethnic groups, z-score of the gender ratio of children under 15 and its interaction with the climate shock; Agro-climatic zone fixed effects. Standard errors clustered at grid level and agro-climatic zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: 2SLS. Short panel. Effect of abundant rainfall on the variation in food security in terms of frequency single items from 2010 pre-harvest to 2011 post-harvest season.

	(1) **Food security 2011**	(2) **Item 1**	(3) **Item 2**	(4) **Item 3**	(5) **Item 4**	(6) **Item 5**	(7) **Item 6**	(8) **Item 7**	(9) **Item 8**	(10) **Item 9**
N. children U15	-0.532	-0.209	0.209	-0.695	-0.480	-0.226	-0.0199	-0.221	-0.0408	-0.0336
	(0.401)	(0.382)	(0.525)	(0.502)	(0.467)	(0.304)	(0.0543)	(0.144)	(0.0926)	(0.0422)
Children*$Rain_{2010}$	0.294	0.0419	-0.138	0.415	0.301	0.189	0.0148	0.125	0.0122	0.0113
	(0.228)	(0.0591)	(0.156)	(0.341)	(0.306)	(0.182)	(0.0399)	(0.0885)	(0.0663)	(0.0277)
$Rain_{2010}$	0.0496*	0.147***	0.0685***	0.00253	0.000802	0.0150	0.00141	-0.00205	0.00990	0.00219
	(0.0284)	(0.0242)	(0.0116)	(0.0392)	(0.0297)	(0.0246)	(0.00843)	(0.00884)	(0.00818)	(0.00321)
Controlling for 2010 levels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ag-eco. zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1250	1216	1232	1221	1205	1208	1196	1201	1197	1198
Dep. var. mean	0.00122	-0.505	-0.348	-0.244	-0.164	-0.176	-0.0154	-0.0336	-0.0290	-0.00630
AP F-test (1)	52.07	143.9	41.11	57.61	64.74	57.59	27.94	43.67	38.15	47.92
p-value	0.00549	0.00125	0.00769	0.00474	0.00401	0.00475	0.0132	0.00706	0.00855	0.00618
AP F-test (2)	114.9	102.3	67.01	57.34	39.48	64.45	76.39	61.77	52.82	77.30
p-value	0.00174	0.00206	0.00381	0.00478	0.00814	0.00404	0.00315	0.00429	0.00538	0.00310

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the $Rain_{2010}$ coefficient for households with the minimum number of young children, one. See notes in Table 9. Dependent variable: scale scores items. I1 = Rely on less preferred foods, I2 = Limit the variety of foods eaten, I3 = Limit portion size at meals-time, I4 = Reduce number of meals eaten in a day, I5 = restrict consumption by adults, I6 = borrow food or rely on help, I7 = have no food, I8 = go to sleep at night hungry, I9 = go a whole day and night without eating; Additional controls: average number of positive shocks 1980-2009, mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, distance in km from population center, age of first-born, z-score gender ratio of children under 15 and its interaction with the climate shock; Agro-climatic zone fixed effects. Standard errors clustered at grid level and agro-climatic zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: 2SLS. Effect of abundant rainfall on the variation in food security in terms of frequency single items from 2011 post-harvest to 2013 post-harvest season.

Dep. var.: Food security 2013 (z-score)	(1)	(2)	(3)	(4)
N. children U15			0.247	0.264
			(0.281)	(0.333)
Children*Rain$_{2010}$			-0.520**	-0.512**
			(0.235)	(0.256)
Rain$_{2010}$	0.0304***	0.0298***	1.066**	1.052**
	(0.00422)	(0.00572)	(0.461)	(0.506)
Food security 2011		0.128***		0.126**
		(0.0421)		(0.0555)
Controls	Yes	Yes	Yes	Yes
Ag.-ecological zone FE	Yes	Yes	Yes	Yes
N	1257	1235	1257	1235
Dep. var. mean		0.0328	0.0268	0.0328
OLS interaction coeff.			0.0111**	0.00949***
S.E. (OLS)			(0.00531)	(0.00343)
AP F-test (1)			265.6	91.12
p-value			0.000503	0.00244
AP F-test (2)			218.4	194.0
p-value			0.000672	0.000801

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the Rain$_{2010}$ coefficient for households with the minimum number of young children, one. See notes in Table 9. Controls: average number of positive shocks 1980-2009, mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, single dummies for each predominant ethnic group, distance in km from population center, age of first-born, z-score gender ratio of children under 15 and its interaction with the climate shock; Agro-ecological zone fixed effects. Standard errors clustered at grid level and Agro-ecological zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: 2SLS. Effect of abundant rainfall on the variation in food security in terms of single items from 2011 post-harvest to 2013 post-harvest season.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Item 1	**Item 2**	**Item 3**	**Item 4**	**Item 5**	**Item 6**	**Item 7**	**Item 8**	**Item 9**
N. children U15	0.296*	0.000562	-0.0399	0.0665	0.0291	-0.244**	-0.321***	0.0342	-0.0832
	(0.178)	(0.233)	(0.102)	(0.297)	(0.0792)	(0.117)	(0.0548)	(0.0743)	(0.113)
Children*Rain$_{2010}$	-0.800***	-0.00217	-0.147	-0.137	-0.295**	0.0790	0.157***	-0.0246	0.0956
	(0.0260)	(0.149)	(0.107)	(0.207)	(0.138)	(0.0963)	(0.0370)	(0.0622)	(0.0780)
Rain$_{2010}$	1.425***	-0.0386	0.303	0.234	0.540**	-0.142	-0.305***	0.0573	-0.184
	(0.0231)	(0.298)	(0.228)	(0.406)	(0.260)	(0.198)	(0.0850)	(0.122)	(0.154)
Control for 2011 levels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ag-eco. zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1220	1233	1221	1216	1218	1206	1208	1206	1208
Dep. var. mean	-0.926	-0.803	-0.513	-0.378	-0.300	-0.134	-0.107	-0.0852	-0.0515
OLS interaction coeff.	0.0172	0.00174	-0.00317	0.00255	-0.0137	-0.0217***	0.0128*	0.00614	0.000605
S.E. (OLS)	(0.0125)	(0.0185)	(0.0135)	(0.00582)	(0.0163)	(0.00176)	(0.00686)	(0.00869)	(0.00344)

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the Rain$_{2010}$ coefficient for households with the minimum number of young children, one. See notes in Table 9. Dependent variable: scale scores items. I1 = Rely on less preferred foods, I2 = Limit the variety of foods eaten, I3 = Limit portion size at meals-time, I4 = Reduce number of meals eaten in a day, I5 = restrict consumption by adults, I6 = borrow food or rely on help, I7 = have no food, I8 = go to sleep at night hungry, I9 = go a whole day and night without eating; Additional controls: average number of positive shocks 1980-2009, mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, single dummies for each predominant ethnic group, distance in km from population center, age of first-born, z-score gender ratio of children under 15 and its interaction with the climate shock; Agro-ecological zone fixed effects. Standard errors clustered at grid level and Agro-ecological zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix

A.1 Magnitude of son-preference effect

The strong predictive power for the sample analysed (young women with children under 15 years old living at home) is what is needed for the validity of the instrument. The sample was selected on purpose, following Angrist and Evans (1998). That said, the magnitude of the coefficient and the implications for son-preference might be of interest in their own right.

The selected sample is by no means fully representative of the total or completed fertility of Nigerian women for two main reasons. First, the mother's age range implies that most mothers have not completed their fertility history. Secondly, the children's age range and living arrangements do not consider all ever born children. Hence, whether these magnitudes are an over or under-estimation of the actual impact of son-preference on fertility behaviour is hard to say given the available data, but might depend mainly on how persistent son-preference is throughout a woman's reproductive life.

These results could be an over-estimation if gender preferences are stronger at the beginning of a woman's reproductive life: having had a female first-born, the immediate pressure for having at least one son could be higher. Once an ideal proportion of sons has been reached, parents may keep having children, though at a lower pace. The effect of son-preference would then predominate in the early reproductive years, decreasing over time.

On the other hand, I might be under-estimating the impact of the first-born gender if son-preference is constant over time and not decreasing once the ideal number of sons has been reached. In this case, mothers with a female first-born will continue to have a higher number of children throughout their reproductive life, irrespectively of the share of sons. These estimates could be a lower bound for those mothers who have not yet reached the ideal number of sons, while they are approaching the end of their reproductive life period. In this case, son-preference would be stronger for older mothers. Table A.17 seems to suggest that son-preference is stronger for young mothers, as the gender of the first-born is not significantly associated with the number of children ever-born (columns 1-2), alive (columns 3-4) or staying in the household (columns 5-6) for the sample of mothers older than 35. Hence, the first-stage results are more likely to be an over-estimation of the son-preference effect on fertility.[55]

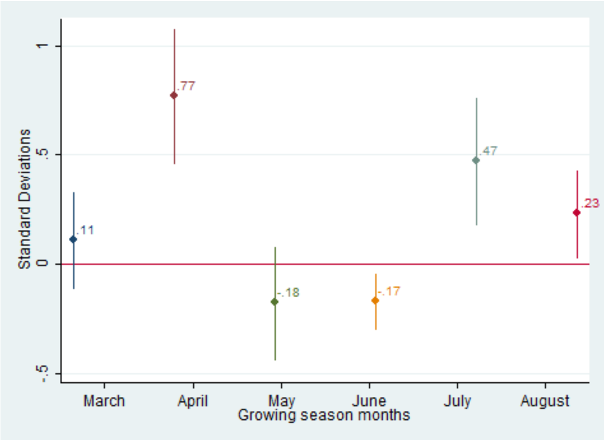
An alternative reason for these estimates being a lower bound could be related to mothers being at the beginning of their reproductive life. If they have some control over their reproductive behaviour, they could wait longer before having another child (for instance by breast-feeding the first-born for a longer time period).[56] I explore this option in the robustness checks section, by interacting the instruments with mother's age.

[55] In the robustness checks section, I run the first-stage with the DHS data, using the same specification as with the LSMS-ISA data, and show that the gender of the first-born still significantly increases the number of children, though the magnitude is lower.

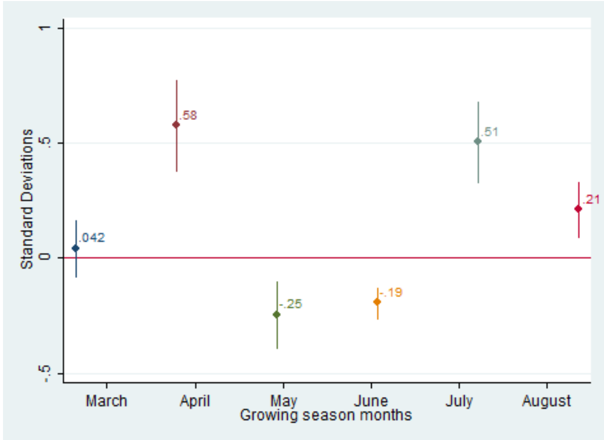
[56] In Nigeria, Milazzo (2014) finds that son-preference increases the number of children ever-born by 2%, which might suggest that my results are an over-estimation compared with the whole birth history of an average Nigerian woman.

Figure A.8: Important growing season months for harvest quantity.

(a) Not adjusting for spatial correlation



(b) Adjusting for spatial correlation



A.2 Food security scale

The food security scale administered in the LSMS-ISA questionnaire contains 9 questions (items) with details about the frequency-of-occurrence of the conditions inquired about. The question is formulated as:

" In the past seven days, how many days have you or someone in your household had to:"

Then follows a list of nine different conditions:

1. Rely on less preferred foods?
2. Limit the variety of foods eaten?
3. Limit the portion size at meal-times?
4. Reduce number of meals eaten in a day?
5. Restrict consumption by adults in order for small children to eat?
6. Borrow food, or rely on help from a friend or relative?
7. Have no food of any kind in your household?
8. Go to sleep at night hungry because there is not enough food?
9. Go a whole day and night without eating anything?

Table A.1: 2SLS. Impact of positive weather shocks on fertility. Mothers under 30.

	First-stage		Second-stage	
	(1)	(2)	(3)	(4)
	N. children U15	**Children* $\mathbf{Rain_{2010}}$**	**N. children dead**	**Newborns**
First born is a girl	0.349*	-0.484*		
	(0.144)	(0.199)		
First-born*$Rain_{2010}$	0.0328	0.828***		
	(0.0871)	(0.121)		
N. children U15			0.00240	0.274***
			(0.0513)	(0.0169)
Children*$Rain_{2010}$			-0.0608**	-0.0827***
			(0.0295)	(0.0125)
$Rain_{2010}$	0.0307	-0.558***	-0.00943	0.0280
	(0.0445)	(0.0475)	(0.00653)	(0.0184)
Mean $Rain_{1980-2009}$	-0.0681	-0.0302	-0.164**	-0.206***
	(0.369)	(0.276)	(0.0783)	(0.0790)
N	819	819	819	819
AP F-test (1)			15.18	15.18
p-value			0.0300	0.0300
AP F-test (2)			39.29	39.29
p-value			0.00820	0.00820

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the $Rain_{2010}$ coefficient for households with the minimum number of young children, one. Controls: mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, distance in km from population center, age of the first-born, set of dummies for ethnic groups, z-score of gender ratio of children under 15 and its interaction with the climate shock; Agro-climatic zone fixed effects. Standard errors clustered at grid level and agro-climatic zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Food security scale. Percentage of affirmative answers before and after the harvest, whole sample.

	(1)	(2)	(3)
	Pre-harvest 2010	Post-harvest 2011	Means-test
rely on less preferred foods	0.382	0.292	-0.0904***
	(0.486)	(0.455)	(0.00988)
limit the variety of foods eaten	0.376	0.266	-0.110***
	(0.485)	(0.442)	(0.00974)
limit the portion size of meals	0.310	0.185	-0.125***
	(0.463)	(0.388)	(0.00897)
reduce number of meals	0.294	0.164	-0.130***
	(0.456)	(0.370)	(0.00872)
restrict consumption by adults for children	0.187	0.0856	-0.102***
	(0.390)	(0.280)	(0.00713)
borrow food or rely on help	0.113	0.0251	-0.0876***
	(0.316)	(0.157)	(0.00524)
have no food of any kind	0.100	0.0333	-0.0668***
	(0.300)	(0.179)	(0.00519)
go to sleep at night hungry	0.106	0.0298	-0.0763***
	(0.308)	(0.170)	(0.00522)
go a whole day an night without eating	0.0618	0.0128	-0.0490***
	(0.241)	(0.112)	(0.00395)
Observations	4534	4534	9068

mean coefficients; sd and se in parentheses. The number of observations refers to panel households interviewed in the two survey waves.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: OLS. Climate shocks on quantity and value of harvest sold (2010/2011)

Harvest sold:	**Tot. Q (kcal)**		**PC Q (kcal)**		**Tot. value**		**PC value**		**Value per kg**		**Value per kg and PC**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Drought_{2010}	-0.229		-0.198		-0.121***		-0.108***		-0.115***		-0.103*	
	(0.414)		(0.345)		(0.0188)		(0.0346)		(0.0375)		(0.0539)	
Rain_{2010}		0.240**		0.172*		0.0281		-0.0132		0.0448		0.00354
		(0.106)		(0.0954)		(0.0855)		(0.0904)		(0.0841)		(0.0890)
Constant	11.29***	10.97***	10.30***	10.07***	-3.307***	-3.368***	-3.131***	-3.133***	2.105***	2.023***	2.282***	2.258***
	(0.895)	(0.989)	(0.741)	(0.753)	(0.755)	(0.636)	(0.696)	(0.565)	(0.518)	(0.421)	(0.474)	(0.380)
Agro-ecological zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2035	2035	2035	2035	1154	1154	1154	1154	1155	1155	1155	1155
Dep. var. mean	8.359	8.359	6.881	6.881	-2.805	-2.805	-4.699	-4.699	3.943	3.943	2.049	2.049
r2	0.0568	0.0569	0.0580	0.0580	0.0433	0.0409	0.0597	0.0578	0.0506	0.0469	0.0509	0.0476

Standard errors clustered at the GPS-cell and Agro-ecological zone level. Dependent variable in cols.1-4 is equal to zero when farmers have produced some harvest but did not sell any; in cols.5-12 the farmers not selling any positive harvest are excluded. Harvest quantity measures are computed with the inverse hyperbolic sine transformation, harvest values are in logarithmic form.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Test for price effects (2010/2011). Negative shock. Community level.

	Prices of:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sorghum	Millet	Maize white	Maize yellow	Cassava	Yam	Plantain	Beans
$Drought_{2010}$	5.270	-0.300	16.54*	5.742***	19.70	27.50	-2.379	20.89
	(6.493)	(2.729)	(9.235)	(2.102)	(41.64)	(18.66)	(27.85)	(27.27)
N	359	378	285	693	223	266	223	200
r2	0.000154	0.00000437	0.00124	0.000127	0.00291	0.00346	0.0000554	0.0000935
F	0.637	0.0117	3.113	7.232	0.217	2.109	0.00703	0.567
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	
	Beef	Fresh fish	Eggs	Rice local	Rice imported	Palm oil	Fresh milk	
$Drought_{2010}$	-47.20	150.0***	-4.975	115.8	191.1	-107.7	-32.04	
	(51.56)	(46.22)	(7.077)	(96.52)	(177.9)	(96.42)	(19.61)	
N	375	184	493	424	324	366	419	
r2	0.00728	0.0703	0.000633	0.00386	0.00633	0.0229	0.00551	
F	0.814	10.17	0.479	1.396	1.120	1.212	2.567	

State fixed effects. Standard errors clustered at the Enumerator Area and State level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Test for price effects (2010/2011). Positive shock. Community level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sorghum	Millet	Maize white	Maize yellow	Cassava	Yam	Plantain	Beans
$Rain_{2010}$	10.27	3.512	-21.52	-19.57	22.11	18.96	54.25*	-11.50
	(28.49)	(4.164)	(19.60)	(13.77)	(18.12)	(12.45)	(31.84)	(7.856)
N	359	378	285	693	223	266	223	200
r2	0.000400	0.000765	0.00142	0.000547	0.00127	0.000841	0.00656	0.0000283
F	0.126	0.686	1.170	1.957	1.444	2.253	2.796	2.067
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
	Beef	Fresh fish	Eggs	Rice local	Rice imported	Palm oil	Fresh milk	
$Rain_{2010}$	-27.71	47.32	-3.728	-5.906	-8.316	60.80	15.74	
	(45.05)	(42.49)	(3.419)	(18.26)	(15.26)	(62.05)	(44.02)	
N	375	184	493	424	324	366	419	
r2	0.00165	0.00448	0.000167	0.00000531	0.00000870	0.00354	0.00167	
F	0.368	1.197	1.153	0.101	0.288	0.933	0.123	

State fixed effects. Standard errors clustered at the Enumerator Area and State level

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Household characteristics by the gender of the first child. Whole sample. DHS 2013

	(1) Mother's education	(2) Mother BMI (z-score)	(3) Father's education	(4) Male head	(5) Wealth index	(6) Muslim	(7) HH size
				A. First ever-born child			
First ever-born is a boy	0.629	-0.351	0.926	0.932	2.332	0.660	6.997
	(0.0718)	(0.0535)	(0.0709)	(0.0102)	(0.105)	(0.0466)	(0.160)
First ever-born is a girl	0.600	-0.289	0.898	0.924	2.248	0.648	6.952
	(0.0661)	(0.0614)	(0.0717)	(0.0132)	(0.0941)	(0.0459)	(0.151)
Diff. girl-boy (means test)	-0.0290	0.0619	-0.0276	-0.00792	-0.0845*	-0.0125	-0.0453
	(0.0381)	(0.0680)	(0.0442)	(0.0116)	(0.0492)	(0.0191)	(0.147)
Observations	11312	2093	11239	11312	11312	11312	11312
				B. First child alive			
First alive is a boy	0.646	-0.373	0.950	0.926	2.359	0.652	7.126
	(0.0715)	(0.0582)	(0.0705)	(0.0123)	(0.106)	(0.0471)	(0.180)
First alive is a girl	0.584	-0.264	0.876	0.930	2.227	0.654	6.892
	(0.0675)	(0.0634)	(0.0719)	(0.0112)	(0.0941)	(0.0459)	(0.148)
Diff. girl-boy (means-test)	-0.0620	0.109	-0.0742*	0.00466	-0.132**	0.00212	-0.234
	(0.0413)	(0.0746)	(0.0439)	(0.0118)	(0.0563)	(0.0215)	(0.179)
Observations	11152	2006	11079	11152	11152	11152	11152
				C. First child in the household			
First in HH is a boy	0.626	-0.362	0.891	0.936	2.316	0.659	7.281
	(0.0693)	(0.0593)	(0.0695)	(0.0113)	(0.101)	(0.0465)	(0.188)
First in HH is a girl	0.600	-0.282	0.935	0.925	2.264	0.654	6.915
	(0.0679)	(0.0645)	(0.0745)	(0.0115)	(0.0985)	(0.0462)	(0.138)
Diff. girl-boy (means-test)	-0.0260	0.0797	0.0444	-0.0111	-0.0516	-0.00570	-0.365*
	(0.0356)	(0.0746)	(0.0490)	(0.0116)	(0.0496)	(0.0197)	(0.186)
Observations	10620	1968	10547	10620	10620	10620	10620

Standard errors in parentheses clustered at the grid level; rural sample only; sampling weights applied. Mother BMI z-score estimated for mothers under 23 years old based on the 1990 British Growth Chart.

Table A.7: Household characteristics by the gender of the first child. Mothers under 35 years old. DHS 2013

	(1) Mother's education	(2) Mother BMI (z-score)	(3) Father's education	(4) Male head	(5) Wealth index	(6) Muslim	(7) HH size
				A. First ever-born child			
First ever-born is a girl	0.607	-0.289	0.923	0.919	2.245	0.676	6.454
	(0.0680)	(0.0614)	(0.0698)	(0.0133)	(0.0901)	(0.0447)	(0.124)
First ever-born is a boy	0.632	-0.351	0.922	0.925	2.270	0.683	6.523
	(0.0703)	(0.0535)	(0.0685)	(0.0111)	(0.101)	(0.0463)	(0.145)
Diff. girl-boy (means-test)	-0.0246	0.0619	0.00166	-0.00584	-0.0255	-0.00755	-0.0697
	(0.0416)	(0.0680)	(0.0439)	(0.0122)	(0.0544)	(0.0235)	(0.165)
Observations	6742	2093	6699	6742	6742	6742	6742
				B. First child alive			
First-born alive is a girl	0.592	-0.264	0.916	0.919	2.228	0.682	6.532
	(0.0693)	(0.0634)	(0.0716)	(0.0135)	(0.0918)	(0.0453)	(0.137)
First-born alive is a boy	0.650	-0.373	0.935	0.924	2.295	0.675	6.526
	(0.0698)	(0.0582)	(0.0710)	(0.0116)	(0.101)	(0.0465)	(0.150)
Diff. girl-boy (means-test)	-0.0574	0.109	-0.0187	-0.00460	-0.0666	0.00740	0.00611
	(0.0441)	(0.0746)	(0.0558)	(0.0132)	(0.0572)	(0.0256)	(0.188)
Observations	6610	2006	6567	6610	6610	6610	6610
				C. First child in the household			
First in the HH is a girl	0.574	-0.282	0.918	0.919	2.211	0.685	6.562
	(0.0677)	(0.0645)	(0.0717)	(0.0131)	(0.0880)	(0.0456)	(0.128)
First in the HH is a boy	0.654	-0.362	0.922	0.931	2.301	0.680	6.604
	(0.0707)	(0.0593)	(0.0716)	(0.0108)	(0.104)	(0.0455)	(0.146)
Diff. girl-boy (means-test)	-0.0797*	0.0797	-0.00401	-0.0120	-0.0903	0.00529	-0.0412
	(0.0437)	(0.0746)	(0.0575)	(0.0127)	(0.0591)	(0.0248)	(0.173)
Observations	6441	1968	6398	6441	6441	6441	6441

Standard errors in parentheses clustered at the grid level; rural sample only; sampling weights applied. Mother BMI z-score estimated for mothers under 23 years old based on the 1990 British Growth Chart.

Table A.8: 2SLS. Effects of the number of children and abundant rainfall on the quantity (log) of produced harvest and the value of sold harvest (2011).

	(1) **Harvest Q (kcal)**	(2) **PC Harvest Q (kcal)**	(3) **Value sold harvest (per kcal)**	(4) **Value PC sold harvest (per kcal)**
N. children U15	-0.648***	-0.735***	-0.734***	-0.778***
	(0.180)	(0.192)	(0.227)	(0.252)
Children*Rain_{2010}	0.600***	0.571***	0.698**	0.543**
	(0.127)	(0.126)	(0.274)	(0.261)
Rain_{2010}	-0.0906	-0.103	-0.00713	-0.0142
	(0.0623)	(0.0702)	(0.0308)	(0.0212)
Mean $\text{Rain}_{1980-2009}$	-0.000789	0.0833	0.0618	0.0449
	(0.408)	(0.403)	(0.344)	(0.432)
Controls	Yes	Yes	Yes	Yes
Agro-ecological zone FE	Yes	Yes	Yes	Yes
N	989	989	592	592

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the Rain_{2010} coefficient for households with the minimum number of young children, one. The dependent variables are expressed in kilocalories and are in the logarithmic form. They equal zero for farmers that planted but did not harvest any crop or that harvested but did not sell any crop. The sample includes only households that have planted at least one crop in the pre-harvest season. The regression concerning the value of sold harvest considers only those that have harvested a non-null quantity; Additional controls: mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, distance in km from population center, age of first-born, set of dummies for ethnic groups, z-score of gender ratio of children under 15 and its interaction with the climate shock; Agro-ecological zone fixed effects. Standard errors clustered at the grid level and Agro-ecological zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Historical trend of climate shocks affecting child mortality and gender selection. 2013 DHS

	(1) **N. of dead children**	(2) **N. dead boys**	(3) **N. dead girls**	(4) **N. dead female first-born**
Rain_{2010}	-0.0365***	-0.0227***	-0.0137***	0.00143
	(0.00291)	(0.00112)	(0.00193)	(0.00121)
Mean $\text{Rain}_{1980-2009}$	-0.156*	-0.0870	-0.0685***	-0.0139***
	(0.0933)	(0.0860)	(0.00739)	(0.00414)
Controls	Yes	Yes	Yes	Yes
Agro-ecological zone FE	Yes	Yes	Yes	Yes
N	6474	6474	6474	6474
N=0	4448	5246	5422	6178
Dep. var. mean	0.531	0.281	0.249	0.0744
r2	0.157	0.104	0.0936	0.0247

Agro-ecological area fixed effects. Standard errors in parentheses clustered at the grid-level and Agro-ecological area. Additional controls: Mother's rank, age and age squared, education, father's education, wealth index, dummy for Muslim, three dummies for main ethnic groups, z-score of gender ratio and its interaction with the weather shock.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: OLS. Negative and positive climate shocks in 2010 affecting the number of newborn and dead children in 2013.

	(1)	(2)	(3)	(4)
	N. children dead	**Newborns**	**N. children dead**	**Newborns**
N. children U15	-0.00149	0.0247***	0.00498***	0.0149***
	(0.00160)	(0.00867)	(0.00132)	(0.00385)
Children*$Rain_{2010}$	0.00352***	-0.00209		
	(0.000690)	(0.00433)		
$Rain_{2010}$	-0.0114***	0.0490***		
	(0.00368)	(0.00144)		
Mean $Rain_{1980-2009}$	-0.0829	-0.191***		
	(0.0691)	(0.0321)		
Children*$Drought_{2010}$			-0.00320	0.0118**
			(0.00254)	(0.00458)
$Drought_{2010}$			-0.00885	-0.0497***
			(0.0110)	(0.00731)
Mean $Drought_{1980-2009}$			0.0407	0.0382
			(0.0346)	(0.0668)
Controls	Yes	Yes	Yes	Yes
Agr-ecological zone FE	Yes	Yes	Yes	Yes
N	1266	1266	1266	1266
Dep. var. mean	0.0504	0.290	0.0504	0.290
r2	0.0299	0.0706	0.0258	0.0622

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the $Rain_{2010}$ coefficient for households with the minimum number of young children, one. Controls: mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, distance in km from population center, age of the first-born, z-score of gender ratio of children under 15 and its interaction with the climate shock; Agro-climatic zone fixed effects. Standard errors clustered at grid level and agro-climatic zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: First stage, positive weather shock. Include all children under 15 years old living at home.

	First stage		Second stage
	N. children U15 (wide)	**N. children (wide)*Rain$_{2010}$**	**Food security 2013**
	(1)	(2)	(3)
First born is a girl	0.368***	0.0335	
	(0.0293)	(0.0611)	
First-born*Rain$_{2010}$	-0.00443	0.309**	
	(0.0336)	(0.0544)	
N. children u15 (wide)			0.0515
			(0.195)
N. children (wide)*Rain$_{2010}$			-0.231*
			(0.125)
Rain$_{2010}$	0.0487**	1.725***	0.445**
	(0.0131)	(0.148)	(0.212)
Food security 2011	-0.136	-0.0633	0.113*
	(0.111)	(0.0908)	(0.0667)
Mean Rain$_{1980-2009}$	-0.601	-0.784**	-0.288
	(0.663)	(0.182)	(0.186)
Controls	Yes	Yes	Yes
Agro-ecological zone FE	Yes	Yes	Yes
N	1235	1235	1235
AP F-test (1)			146.1
p-value			0.00122
AP F-test (2)			33.10
p-value			0.0104

Controls: mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, distance in km from population center, age of first-born, z-score gender ratio of children under 15 and its interaction with the climate shock; Agro-ecological zone fixed effects. Standard errors clustered at grid level and Agro-ecological zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: 2SLS. Positive weather shocks affecting the number of newborn and dead children. 2013 DHS

	(1) N. dead children	(2) Newborn
N. children U15	0.0810	0.450
	(0.337)	(0.500)
Children*Rain	-0.201**	-0.333*
	(0.0953)	(0.175)
$Rain_{2010}$	0.375**	0.615**
	(0.172)	(0.311)
Mean $Rain_{1980-2009}$	-0.0201	0.0189
	(0.0146)	(0.0746)
N	6162	6162
Dep. var. mean	0.123	0.703
AP F-test (1)	6.854	6.854
p-value	0.0791	0.0791
AP F-test (2)	86.27	86.27
p-value	0.00264	0.00264

Agro-ecological area fixed effects. Standard errors in parentheses clustered at the agro-ecological area. Additional controls: Mother's rank, age, education, father's education, wealth index, dummy for Muslim.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.13: First-stage using the Nigeria 2013 DHS. Gender of first child (ever-born/alive/in the household).

	N. Ever-born		N. Alive U15		N. In hh U15	
	(1)	(2)	(3)	(4)	(5)	(6)
First ever-born is a girl	0.113**	0.0768				
	(0.0311)	(0.0632)				
First ever-born*$Rain_{2010}$		0.0369				
		(0.0173)				
First alive is a girl			0.157**	0.174**		
			(0.0380)	(0.0437)		
First alive*$Rain_{2010}$				-0.0180		
				(0.0134)		
First in HH is a girl					0.117***	0.130***
					(0.0128)	(0.0212)
First in HH*$Rain_{2010}$						-0.0132
						(0.0127)
$Rain_{2010}$	-0.0163**	-0.0338***	0.0191*	0.0276***	0.00747	0.0138
	(0.00385)	(0.00502)	(0.00783)	(0.00314)	(0.0133)	(0.00981)
Constant	-2.030**	-2.001**	-3.039*	-3.051**	-2.771**	-2.781**
	(0.424)	(0.410)	(0.959)	(0.950)	(0.771)	(0.764)
N	6474	6474	6474	6474	6321	6321
Dep. var. mean	3.351	3.351	2.734	2.734	2.548	2.548
r2	0.510	0.510	0.406	0.406	0.349	0.349
Instruments F-test	13.23	267.9	17.03	117.6	83.66	3308.5

Dependent variable: number of children ever-born, alive (under 15) and currently living at home (under 15). Additional controls: mothers' rank, education, age and age squared, wealth index, father's education, dummy for Muslim, three dummies for main ethnic groups, z-score gender ratio of children under 15 and its interaction with the climate shock; Agro-ecological zone fixed effects. Standard errors clustered at grid level and Agro-ecological zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.14: First stage, positive weather shock (alternative specification).

Dep. var.: N. children U15	(1)	(2)	(3)	(4)	(5)	(6)
First born is a girl	0.0398	0.120**	0.203***	0.207***	0.209***	0.199***
	(0.0891)	(0.0346)	(0.0134)	(0.00835)	(0.00808)	(0.0280)
First-born*Rain$_{2010}$						0.00727
						(0.0270)
Rain$_{2010}$						0.146***
						(0.0241)
Parents controls	No	Yes	Yes	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	Yes	Yes
Age of first-born interacted	No	No	No	Yes	Yes	Yes
Ethnic groups dummies	No	No	No	No	Yes	Yes
Agro-eco. zone FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1356	1286	1281	1277	1277	1277
N. clusters	163	163	163	162	162	162
Instrument F-test	0.200	12.06	228.2	614.8	666.6	286.5

See notes in Table 9. Parents controls: average number of positive shocks 1980-2009, mothers' rank, education, age and age squared, father's education; Household controls: total value of assets, dummy for Muslim, distance in km from population center, age of the first-born; Agro-ecological zone fixed effects. Standard errors clustered at grid level and Agro-ecological zone in parentheses. Sample weights applied

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.15: 2SLS. Effect of abundant rainfall on the variation in food security from 2011 to 2013 post-harvest season, controlling for 2012 rainfall shocks.

Dep. var.: Food security 2013 (z-score)	(1)	(2)	(3)	(4)
N. children U15			0.246	0.264
			(0.286)	(0.338)
Children*Rain$_{2010}$			-0.515**	-0.512*
			(0.248)	(0.272)
Rain$_{2010}$	0.0415***	0.0387***	0.0751***	0.0748***
	(0.00235)	(0.00177)	(0.00779)	(0.0118)
Rain$_{2012}$	0.0918***	0.0733***	0.0191	0.0000488
	(0.00385)	(0.00478)	(0.0433)	(0.0550)
Food security 2011		0.122***		0.124**
		(0.0429)		(0.0566)
N	1257	1235	1257	1235
Dep. var. mean		0.0328	0.0268	0.0328
AP F-test (1)			44.06	37.42
p-value			0.00697	0.00878
AP F-test (2)			120.8	116.7
p-value			0.00161	0.00170

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the Rain$_{2010}$ coefficient for households with the minimum number of young children, one. See notes in Table 9. Dependent variable: z-score of food security score. Controls: average number of positive shocks 1980-2009, mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, distance in km from population center, age of first-born, set of ethnic group dummies, z-score gender ratio of children under 15 and its interaction with the climate shock; Agro-ecological zone fixed effects. Standard errors clustered at grid level and Agro-ecological zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.16: 2SLS. Effect of abundant rainfall on food security variation between the 2010 to 2012 pre-harvest seasons.

Dep. var.: Food security 2012 (z-score)	(1)	(2)	(3)	(4)
N. children U15			0.217	0.160
			(0.247)	(0.244)
Children*Rain$_{2010}$			-0.457**	-0.421**
			(0.207)	(0.188)
Rain$_{2010}$	0.0267***	0.0401***	0.0643***	0.0744***
	(0.00370)	(0.00563)	(0.0107)	(0.0130)
Food security 2010		0.0769***		0.0658*
		(0.0277)		(0.0361)
N	1257	1248	1257	1248
Dep. var. mean		0.0999	0.101	0.0999
AP F-test (1)			42.63	36.24
p-value			0.00730	0.00919
AP F-test (2)			159.1	197.2
p-value			0.00108	0.000782

The number of children U15 is standardised as n. children U15 - 1, so to make the interpretation of the Rain$_{2010}$ coefficient for households with the minimum number of young children, one. See notes in Table 9. Dependent variable: z-score of food security score. Controls: average number of positive shocks 1980-2009, mothers' rank, education, age and age squared, total value of assets, father's education, dummy for Muslim, distance in km from population center, age of first-born, set of ethnic group dummies, z-score gender ratio of children under 15 and its interaction with the climate shock; Agro-ecologic zone fixed effects. Standard errors clustered at grid level and agro-ecologic zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.17: First-stage using the Nigeria 2013 DHS, mothers over 35 years old. Gender of first child (ever-born/alive/in the household).

	N. Ever-born		**N. Alive U15**		**N. In hh U15**	
	(1)	(2)	(3)	(4)	(5)	(6)
First ever-born is a girl	-0.00785	0.0166				
	(0.0287)	(0.0385)				
First ever-born*Rain_{2010}		-0.0277				
		(0.0241)				
First-born alive is a girl			-0.0451	-0.00897		
			(0.111)	(0.128)		
First-born alive*Rain_{2010}				-0.0409		
				(0.0404)		
First in HH is a girl					-0.110	0.0232
					(0.129)	(0.0911)
First in HH*Rain_{2010}						-0.153**
						(0.0302)
Rain_{2010}	-0.0434	-0.0310	-0.0117	0.00758	-0.0384	0.0162
	(0.0293)	(0.0198)	(0.0517)	(0.0334)	(0.0506)	(0.0471)
Mean $\text{Rain}_{1980-2009}$	-0.246	-0.247	0.0758	0.0742	0.103	0.0869
	(0.330)	(0.330)	(0.120)	(0.120)	(0.0957)	(0.101)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Agro-ecological zone FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3374	3374	3374	3374	3245	3245
Dep. var. mean	7.215	7.215	3.181	3.181	2.859	2.859
Instruments F-test	0.0748	45.65	0.166	33.54	0.724	32.44

Dependent variable: number of children ever-born, alive (under 15) and being currently at home (under 15). Additional controls: mothers' rank, education, age and age squared, wealth index, father's education, dummy for Muslim, three dummies for main ethnic groups, z-score of gender ratio of children under 15 and its interaction with the weather shock; Agro-ecological zone fixed effects. Standard errors clustered at grid level and Agro-ecological zone in parentheses. Sample weights applied.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$